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Universidad del País Vasco
Euskal Herriko Unibertsitatea

INFORMATIKA FAKULTATEA
FACULTAD DE INFORMÁTICA

Departamento de Ciencia de la Computación e Inteligencia Artificial

TESIS DOCTORAL

Soluciones innovadoras basadas en manipuladores móviles para el nuevo paradigma de fabricación flexible en el marco de la Industria 4.0

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Dirección: Basilio Sierra, Iván Villaverde

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Dirección

Iván Villaverde de la Nava
Basilio Sierra Araujo

19 de junio de 2024

"Tanto la robótica como la inteligencia artificial son herramientas cuyo fin es asistir y ayudar al ser humano. Cuanto antes nos demos cuenta de ello y las utilicemos con conocimiento, antes progresaremos hacia un futuro con grandes avances."

"Cada revolución industrial se ha percibido con desconfianza a lo nuevo y desconocido, no obstante, han supuesto un gran avance tecnológico y disruptivo que ha favorecido a todos los procesos industriales."

Jose Luis Outón, apasionado por la
Robótica y la Industria

Agradecimientos

¡Y por fin llegó el gran día! Ese día que tantas veces he imaginado pero que tanto tiempo me ha costado alcanzar. Como seguro que mis predecesores compartirán conmigo, la tesis no comienza cuando formalizas los papeles de acceso y firmas la matrícula. En mi opinión, este proceso comienza mucho antes. Me atrevería a decir que empieza cuando, en tus últimos años de carrera, eres consciente de que con tu trabajo y esfuerzo puedes añadir un pequeño granito de arena más a la investigación. Justo en ese momento en el que nace en ti una ilusión por colaborar y aportar tu conocimiento y resultados a la ciencia. Ahí es cuando te das cuenta que estás, en cierta medida, predestinado a realizar esta aventura que denominan tesis doctoral.

Como comentaba, durante los últimos años de carrera, cuando ya posees una visión más completa y global del mundo académico y la investigación, se me pasó muchas veces por la cabeza la idea de hacer un mundo mejor, un mundo donde la tecnología ayude a las personas a que sus vidas sean un poco más fáciles. Es por ello, que tomé la decisión de formarme, trabajar e investigar en Robótica, un campo relativamente nuevo y con un gran potencial de crecimiento y futuro. Considero que la robótica es una herramienta capaz de ayudar, asistir y favorecer a los humanos con la que construiremos un mundo más avanzado, conectado y eficiente.

Hablando un poco más de mi, me gustaría resaltar una forma de ser muy diplomática que me caracteriza a la hora de tomar decisiones. Éstas, siempre las suelo tomar consensuando con mi familia y valorando las ventajas y desventajas de cada nueva oportunidad que se me presenta. Es por ello que, a finales de 2008, justo cuando estaba finalizando la Ingeniería Técnica en Informática de Sistemas, se me planteaba un futuro incierto. Pero, en ese mismo instante, tras consultarlo con mi familia, una vocecilla llamada "mamá" me sugirió realizar la Ingeniería Superior. Tras analizarlo, así lo hice, ya que me parecía una buena oportunidad y me abriría puertas en el futuro. Pero, esto no acabó aquí, ya que, pasados dos años, esa misma voz volvió a sugerirme que sería muy interesante hacer un máster, tan demandado y necesario en nuestros días. Parece ser que esa voz de madre

caló en lo más profundo de mi ser y cuando me quise dar cuenta ya estaba matriculado en el máster KISA de la Facultad de informática de San Sebastián. Al finalizar el primer año, una vez más, esa misma voz volvió a susurrar mis oídos proponiéndome un pasito más, el último paso para cerrar el ciclo. Bueno, pues aquí estoy ahora, escribiendo los agradecimientos de mi tesis doctoral.

Por todo ello y mucho más, me gustaría agradecer a mi madre el apoyo incondicional y el empuje constante que me incentivó en cada etapa de mi vida a luchar por un poquito más. Siempre con una actitud positiva, animándome y allanándome el camino para que todo me resultara más fácil. Por todo ello, **esto va por ti, mamá.**

Me gustaría hacer una mención muy especial a la persona que más feliz me hace. Mi compañera de vida, Nagore. Por todo lo que me enseña día a día sin darse cuenta y por lo que vamos construyendo juntos, una gran familia. Y, por último, mencionar a mi referente y ejemplo de vida. No puedo estar más orgulloso de ti, Abuelo.

Todo esto no podía haber sido posible sin el apoyo de mis dos grandes instituciones: Tecnalia y UPV/EHU. Gracias por brindarme esta gran oportunidad. Concretamente me gustaría agradecer a mis compañeros de Tecnalia por todo el apoyo y la ayuda en los innumerables proyectos que hemos desarrollado juntos y sobre todo a mi compañero y mentor, Iván Villaverde. No sabes todo lo que me has enseñado durante estos años, mucho más allá de la tesis. Y a ti también Basilio Sierra, por tu actitud positiva e ímpetu para que entrara en el plan de doctorado.

¡Muchas gracias!

Resumen

Al analizar la situación actual y las tendencias futuras de la industria, en particular en las plantas de producción y fabricación, se pueden identificar diversos factores que están cambiando la industria tal y como la conocemos. Existe un cambio de paradigma en las necesidades actuales de la fabricación que está provocando una transición del enfoque actual basado en la producción en masa a un enfoque de gran personalización (*mass costumization*), donde los volúmenes de producción son más pequeños y variables. Los procesos actuales están muy adaptados al paradigma anterior y carecen de la flexibilidad necesaria para adaptarse a las nuevas necesidades de producción. Además se ha de añadir una disminución en la disponibilidad de operadores capacitados debido al envejecimiento de la población. Adaptarse a este nuevo escenario representa un desafío para las empresas, especialmente las pequeñas y medianas empresas (Pymes), que están experimentando cómo su especialización se vuelve en su contra de manera evidente.

El objetivo de este trabajo es mitigar los efectos de este cambio de paradigma en la industria mediante la inclusión de soluciones robotizadas flexibles en los procesos productivos. Concretamente se presenta inicialmente una revisión de la literatura sobre manipuladores móviles autónomos y sus aplicaciones en diferentes campos industriales que sirve como base para el trabajo desarrollado. Este trabajo realiza contribuciones en los siguientes campos de estudio, avalados por publicaciones en revistas de alto impacto:

- Industria 4.0
- Robótica móvil
- Percepción artificial
- Navegación autónoma
- Robótica colaborativa
- Fusión de sensores
- AIMMs (*Autonomous Industrial Mobile Manipulators*)

Laburpena

Industriaren egungo egoera eta etorkizuneko joerak aztertuz, bereziki ekoizpen eta fabrikazio lantegietan, industria ezagutzen dugun bezala aldatzen ari diren hainbat faktore identifikatu daitezke. Fabrikazioaren egungo beharretan paradigma-aldaketa bat dago, produkzio masiboan oinarritutako egungo ikuspegitik pertsonalizazio masiboko ikuspegira trantsizioa eragiten ari dena, non produkzio bolumenak txikiagoak eta aldagarriak diren. Egungo prozesuak oso egokituta daude aurreko paradigmara eta ez dute beharrezko malgutasunik produkzio-behar berrietara egokitzeko. Horrez gain, gutxitu egiten da trebatutako operadoreen erabilgarritasuna biztanleriaren zahartzearen ondorioz. Eszenatoki berri horretara egokitzea erronka bat da enpresentzat, batez ere enpresa txiki eta ertainentzat (ETE), zeinak argi eta garbi jasaten ari diren espezializazioa haien aurka egiten duela.

Lan honen helburua industrian paradigma aldaketa honen ondorioak arintzea da, ekoizpen prozesuetan malguko robotika soluzioak sartuz. Zehazki, manipulatzaile mugikor autonomoei eta industria-eremu ezberdinetan dituzten aplikazioei buruzko literaturaren berrikuspena aurkezten da, garatutako lanerako oinarri gisa balio duena. Lan honek ikerketa-eremu hauetan ekarpenak egiten ditu, eragin handiko aldizkarietako argitalpenek lagunduta:

- Industria 4.0
- Robotika mugikorra
- Pertzepzio artifiziala
- Nabigazio autonomoa
- Elkarlaneko robotika
- Sensor fusion
- AIMMak (*Autonomous Industrial Mobile Manipulators*)

Abstract

By analyzing the current situation and future trends in the industry, particularly in production and manufacturing plants, various factors can be identified that are changing the industry as we know it. There is a paradigm shift in the current needs of manufacturing that is causing a transition from the current approach based on mass production to a mass customization approach, where production volumes are smaller and variable. Current processes are highly adapted to the previous paradigm and lack the necessary flexibility to adapt to new production needs. In addition, there is a decrease in the availability of trained operators due to the aging of the population. Adapting to this new scenario represents a challenge for companies, especially small and medium-sized companies (SMEs), which are clearly experiencing their specialization turning against them.

The objective of this work is to mitigate the effects of this paradigm shift in the industry by including flexible robotic solutions in production processes. Specifically, first a review of the literature on autonomous mobile manipulators and their applications in different industrial fields is presented as a basis of the work carried out. This work has made several contributions in the following fields of study, supported by publications in high-impact journals:

- Industry 4.0
- Mobile Robotics
- Artificial perception
- Autonomous navigation
- Collaborative robotics
- Sensor fusion
- AIMMs (*Autonomous Industrial Mobile Manipulators*)

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Parte I

Memoria de Tesis

Introducción 1

1.1. Introducción

La base conceptual sobre la que se sustenta este trabajo es la necesidad actual de la industria de enfrentarse al problema conocido como "*High-mix / Low-volume*" [1], entendiendo como tal la necesidad de poder producir series cortas de productos con gran variabilidad.

Inicialmente, la automatización en la industria se orientó hacia la productividad y repetibilidad. Es decir, fabricar series largas de productos idénticos mediante una automatización orientada a maximizar el flujo, limitando el tipo de productos que se pueden manipular, para lograr así sistemas optimizados que permitan trabajar a un gran ritmo. Sin embargo, este paradigma, que ha sido de gran éxito en los últimos 100 años, carece de la flexibilidad necesaria para afrontar con eficacia la demanda actual, caracterizada por el anteriormente mencionado problema de *High-mix/Low volume*. Por ello, actualmente, existe una tendencia creciente hacia una nueva automatización enfocada a una mayor versatilidad, adaptabilidad y capacidad de gestión de series cortas. La adaptación a este nuevo paradigma productivo, recientemente conocido como "personalización masiva" [2], es clave para mantener la competitividad de las empresas manufactureras.

Como describe Nye [3] en su trabajo consistente en una revisión comparativa de 100 años de evolución industrial, asegura que las líneas de montaje actuales son más productivas que nunca gracias a la robótica. Sin embargo, muchos procesos repetitivos y de bajo valor añadido aún pueden y deben automatizarse [4]. Esta falta de automatización en ciertas tareas, generalmente realizadas por operadores poco cualificados, ha sido causada principalmente por el costo que supone reemplazar operadores de bajos salarios por caros sistemas automatizados.

La robótica tradicional, con sus autómatas programables de gran repetibilidad, no logra dar respuesta a la demanda actual del mercado, muy cambiante y basado en la fabricación de pequeños lotes personalizados. La robustez y eficiencia del modelo de producción en serie está altamente comprometida por la necesidad de realizar cambios en los equipos de producción, que carecen de las capacidades cognitivas para soportar múltiples operaciones en un entorno dinámico [5]. Esto se debe a la falta de adaptabilidad de los robots tradicionales y al alto coste que supone cambiar de una tarea a otra diferente, que requieren cambios muy invasivos en la planta de producción a la vez que largos tiempos de programación por parte de especialistas cualificados. Además, sustituir a los actuales operadores poco cualificados por otros de mayor cualificación es una tarea difícil y con un alto coste asociado. Por ello, en la actualidad, los nuevos paradigmas educativos [6] se han centrado en la formación de estos operadores para alcanzar altos grados de cualificación y especialización. Sin embargo, el rápido desarrollo tecnológico, el envejecimiento y la escasa rotación de la masa productiva dificultan esta tarea. La industria busca alternativas y requiere de nuevas soluciones modernas para asistir a los operadores y proporcionar entornos de trabajo colaborativos con los sistemas de producción avanzados [7]. Se espera que esta transformación industrial, basada en la introducción de la robótica moderna y flexible, sea capaz de impulsar un crecimiento del empleo global del 1,36 % [8]. Los últimos informes revelan que al menos el 85 % de las tareas de producción en los principales sectores industriales como la informática, los equipos electrónicos, los medios de transporte y la maquinaria industrial son automatizables [9].

El auge de los sistemas autónomos y la robótica, especialmente los robots colaborativos, está abriendo nuevas posibilidades de mercado; una nueva tendencia hacia la robótica flexible y colaborativa se está extendiendo en la industria en forma de novedosos sistemas denominados Manipuladores Móviles Industriales Autónomos (*Autonomous Industrial Mobile Manipulator* o AIMM por sus siglas en inglés) [10].

1.1.1. Estructura de la memoria

Esta memoria está divida en dos grandes partes, siendo la Parte I la que contextualiza y enmarca la investigación realizada. A su vez, esta primera parte de la memoria está estructurada en secciones, habiendo un total de seis: introducción, motivación, antecedentes y marco de trabajo, nuevo paradigma, Industria 4.0 y robótica autónoma y flexible, contribuciones y, por último, conclusiones.

La primera sección 1, introduce y pone en contexto el contenido del trabajo de tesis dentro del paradigma industrial actual. La sección 2 describe la motivación para realizar este trabajo de tesis y enumera los retos y objetivos abordados. Seguido se encuentra la sección 3 donde se especifican y enmarcar los antecedentes del autor que le han llevado a la realización del trabajo, junto a los proyectos que han avalado la investigación realizada. La sección 4 detalla el estado del arte en un contexto de fabricación industrial, automatización e introducción de la robótica autónoma y flexible en los procesos productivos. La sección 5 enumera las principales contribuciones realizadas a lo largo de la realización de la tesis, principalmente mediante artículos publicados, asistencia a congresos y patentes. Por último, la sección 6 resume el trabajo de tesis con las conclusiones obtenidas y describe el trabajo futuro a realizar.

La Parte II adjunta todos los artículos publicados que avalan el trabajo de tesis.

Motivación 2

2.1. Motivación

Esta tesis se enmarca dentro de uno de los retos generados debido al nuevo paradigma industrial de personalización masiva que se está introduciendo como parte del concepto Industria 4.0. Como hemos visto antes, la actual demanda de productos personalizados está forzando un cambio de paradigma en la industria manufacturera hacia el modelo conocido como *mass customization*. Los actuales métodos de producción se basan en células y líneas de fabricación que repiten una secuencia lineal para optimizar la fabricación de un producto concreto, pero carecen de la flexibilidad necesaria para fabricar de forma eficiente pequeños lotes de productos o introducir nuevas referencias. Para obtener esta flexibilidad en las líneas de producción robotizadas, los robots han de ser versátiles, autoconfigurables e independientes de las líneas. Deben poseer la capacidad de realizar diversas tareas, cambiar de ubicación, adaptarse a las secuencias de producción, interaccionar con otros robots u operarios humanos e incluso reemplazar a otros robots en caso de avería. Fruto de esta tendencia, en los últimos años se ha desarrollado el concepto de "robótica flexible", aplicado a los entornos industriales como una herramienta que permite la implementación de los requerimientos de los procesos de *mass customization*. La robótica flexible trata de combinar información del proceso y la percepción del entorno en sistemas versátiles de navegación, manipulación e interacción humano-robot, apoyados en un marco de trabajo que permita la configuración y programación auto o semi-automática de los robots. Paralelamente, el desarrollo del hardware de los robots ha seguido la tendencia de dotar a estos de mayor versatilidad, intentando darle capacidades más similares a los operarios humanos. Así, en los últimos años se ha incrementado notablemente el desarrollo de robots colaborativos con sensores de par, robots bibrazos o manipuladores móviles industriales.

2.1.1. Retos y Objetivos

Las tareas y fundamentos a investigar y desarrollar en este proyecto de tesis se resumen en los siguientes objetivos:

- Programación de robots fácil

  Las tareas de programación de los sistemas robóticos a día de hoy son procesos muy costosos y que requieren de altos conocimientos de programación y del lenguaje específico del robot a utilizar. Se pretende crear interfaces gráficas de usuario sencillas e intuitivas de modo que cualquier usuario sea capaz de crear y desarrollar un proceso robótico de un modo fácil y eficiente. A su vez se pretende aportar y mejorar, en lo posible, las técnicas de "aprendizaje por demostración" que se están investigando en la actualidad. La combinación de las dos técnicas de programación sencilla dotará a los sistemas robóticos de una mayor versatilidad y facilidad de programación por cualquier usuario no experto.

- Robótica colaborativa

  Las empresas y organismos de ámbitos tecnológicos y de servicios, poseen tareas a desempeñar de carácter repetitivo, costoso, de bajo valor añadido y perjudiciales para el operario que las desempeña. Por ello, se pretende incorporar sistemas robóticos que realicen dichas tareas y que sean capaces de cooperar y adaptarse al medio compartido con personas. Esto conlleva al estudio de un minucioso plan de riesgos, sistemas de percepción y ciclos de control robustos.

- Manipulación flexible

  Los sistemas actuales de manipulación se basan en producción por grandes lotes y sin alteraciones frecuentes de los productos; por tanto, son sistemas muy dedicados y poco flexibles. Este tipo de producción ha cambiado y se requiere la fabricación en lotes pequeños, con muchas variantes en el producto y cuyo proceso productivo no es espacialmente continuo dentro de la planta de producción, dividida en células de trabajo. De aquí nace la necesidad de aplicar manipuladores móviles y flexibles con capacidades autónomas de cambio de tarea, herramientas y aplicaciones, mediante técnicas de percepción.

- Inspección y control de calidad automáticos

  Los procesos de inspección y control de calidad son rutinarios y repetitivos. Los controles varían en función de las capacidades personales variantes en el tiempo y los criterios subjetivos del examinador. Los sistemas de percepción parametrizados según normas de calidad ISO, proporcionan un control de calidad objetivo, fiable y con una mínima tasa de error.

- Sistemas versátiles para navegación autónoma

  Las plantas de producción industrial, los grandes almacenes de productos y los servicios como hospitales y residencias, se encuentran en constante cambio. Es por ello que sistemas de navegación guiados no son una buena solución ya que son invasivos y estáticos (navegación mediante balizas, navegación mediante seguimiento de líneas o tiras magnéticas). Por tanto, se da la necesidad de proporcionar soluciones robóticas móviles dinámicas, autónomas y con capacidad de tomar decisiones en tiempo real. Diferentes investigaciones han desarrollado técnicas de navegación basada en sensores (láser, ultrasonidos, visión 2D/3D) que son capaces de realizar un mapa del entorno en el que van a navegar y localizarse en él [SLAM]. Además, con la ayuda de los sensores, estos sistemas tienen la capacidad de planificar rutas entre diferentes objetivos y esquivar obstáculos estáticos y dinámicos, como pueden ser personas.

- Interacción humano-robot

  La interacción entre el robot y los humanos no solo se basa en compartir el mismo espacio de trabajo, sino también en cooperar y compartir recursos. Desde aplicaciones de robots de servicio que llevan las comidas y suministran los medicamentos a personas dependientes, hasta la antes mencionada robótica colaborativa, en la que los robots colaboran y comparten herramientas con operarios en el montaje de diferentes productos. Se da la necesidad de incorporar multitud de sistemas de percepción y seguridad que reduzcan al mínimo el riesgo de daño a los humanos, teniendo el robot una serie de reglas alimentadas con los datos proporcionados por los sensores que debe cumplir en todo momento.

- Percepción multimodal

  "En la variedad está el gusto" y más es así en los sistemas de percepción. Las investigaciones recientes apuntan a sistemas que comparten diferentes sensores y fusionan sus datos para obtener valores más acertados, precisos y con menor incertidumbre. En este contexto, la percepción multimodal se puede y debe aplicar a cada uno de los objetivos anteriormente citados.

3 Antecedentes y marco de trabajo

La realización de este trabajo se enmarca dentro de la colaboración entre la UPV/EHU y TECNALIA. Esta iniciativa surge gracias al programa de fomento de nuevos doctorandos de TECNALIA y a la oferta de programas de doctorado de excelencia de la UPV/EHU, junto a las ganas y motivación investigadora del autor.

Ante la presente necesidad de dar respuesta a los retos detallados en el capítulo 2, el autor se ha apoyado en los proyectos de investigación en los que TECNALIA forma parte y están directamente relacionados con el nuevo paradigma industrial y al uso de soluciones robotizadas en sus procesos productivos.

En las próximas secciones de este capítulo se describe tanto a la UPV/EHU como a TECNALIA, además de los proyectos más relevantes donde el autor ha realizado sus investigaciones y desarrollos.

3.1. UPV-EHU

La Universidad del País Vasco (UPV/EHU) [11], conocida en euskera como "Euskal Herriko Unibertsitatea," es una institución académica de prestigio ubicada en el País Vasco. Fundada en 1980, la UPV/EHU tiene una historia rica y una sólida reputación en la educación superior y la investigación.

La UPV/EHU tiene campus distribuidos en tres provincias del País Vasco: Álava, Vizcaya y Guipúzcoa. Cada campus está ubicado estratégicamente en ciudades como Vitoria-Gasteiz, Bilbao y Donostia-San Sebastián, lo que proporciona a los estudiantes un entorno diverso y culturalmente enriquecedor. Es reconocida por su destacada labor de investigación en diversos campos. Sus equipos de investigación participan en proyectos nacionales e internacionales, contribuyendo al avance del conocimiento y la innovación en áreas como la ciencia y la tecnología, la medicina, las ciencias sociales y las humanidades.

La Universidad del País Vasco (UPV/EHU) cuenta con la Facultad de Informática en su campus de Donostia-San Sebastián. La facultad ofrece una variedad de programas académicos en el campo de la informática, incluyendo programas de grado y postgrado. Estos programas pueden abarcar áreas como la ingeniería informática, ciencia de datos, inteligencia artificial, sistemas de información, entre otros.

Desde el inicio de su formación académica superior, el autor ha estado vinculado a la UPV/EHU realizando las carreras de Ingeniería Técnica en Informática de Sistemas e Ingeniería en Informática. A su vez, realizó el máster denominado Ingeniería Computacional y Sistemas Inteligentes, que fue el trampolín para embarcarse en la realización de sus tesis doctoral. Durante los últimos años ha colaborado con el grupo de Robótica y Sistemas Autónomos (RSAIT) en diversos proyectos de investigación aplicada.

3.2. TECNALIA

La Fundación Tecnalia Research & Innovation [12] es una organización de investigación aplicada con sede en España y una de las mayores de Europa. Actualmente parte del BRTA (Basque Research And Technology Alliance), surgió en 2011 como la fusión de ocho centros tecnológicos históricos de la CAPV y se dedica a la generación y aplicación de conocimiento científico y tecnológico para impulsar la innovación y el desarrollo en diversos sectores. Su enfoque abarca áreas como energía, industria, movilidad, construcción, salud y sostenibilidad.

TECNALIA trabaja en colaboración con socios industriales, instituciones académicas y otras organizaciones de investigación para abordar desafíos técnicos y científicos complejos. A través de su enfoque multidisciplinario, TECNALIA desarrolla soluciones innovadoras y brinda asesoramiento a sus clientes en áreas como tecnologías avanzadas, procesos industriales, materiales, diseño de productos y estrategias de mercado.

TECNALIA se esfuerza por impulsar la competitividad de las empresas y contribuir al desarrollo económico y social mediante la transferencia de conocimiento y la promoción de la colaboración entre la investigación y la industria. Su trabajo abarca desde la conceptualización de ideas hasta la implementación práctica, ayudando a sus clientes a mejorar su eficiencia, desarrollar nuevos productos y procesos, y afrontar los retos emergentes en un entorno tecnológico en constante evolución.

Durante los años de desarrollo de la tesis, el autor ha tenido la oportunidad de trabajar en multitud de proyectos de investigación de diversa índole, en los cuales ha podido aplicar los conceptos, ideas y tecnologías que fundamentan y avalan la investigación presentada. A continuación, se detallan algunos de los proyectos en los que ha aportado con sus investigaciones.

3.3. Proyectos europeos de investigación

3.3.1. Autorecon

Proyecto AUTORECON [13] (AUTOnomous co-operative machines for highly RE-CONfigurable assembly operations of the future).

En la actualidad, muchos sectores industriales siguen utilizando una serie fija y lineal de operaciones donde las tareas, tanto manuales como automatizadas, se repiten cada ciclo de la manera más eficiente posible. Esta forma de trabajar es muy efectiva cuando la producción se encuentra en su máxima capacidad y siempre que no haya interrupciones debido a problemas técnicos. Sin embargo, esta metodología se vuelve ineficiente cuando las líneas de producción se sienten saturadas. Incluso las líneas de producción más flexibles siguen basándose en este mismo enfoque secuencial jerárquico. La flexibilidad en este contexto se refiere a la capacidad de combinar diferentes procesos, aunque aún sean secuenciales, para diferentes variantes de productos en la misma planta.

El propósito de AUTORECON es revolucionar este paradigma establecido. En una misma instalación, se busca cambiar la secuencia introduciendo unidades de producción/manipulación autónomas capaces de cambiar de tarea y de posición. Estas unidades podrían eventualmente colaborar entre sí, basándose en las secuencias de procesos actuales. Además, siempre tendrían la capacidad de solucionar posibles errores en robots/herramientas al cambiar su posición/tarea, reconfigurándose automáticamente junto con las herramientas y la línea de producción. Todo esto permitiría una respuesta rápida ante la detención de la producción y una reducción de las pérdidas tanto como sea posible.

Para ello, se propone el desarrollo de:

- Unidades de producción autónomas, intercambiables y móviles
- Estructuras robóticas altamente interactivas
- Flujos de producción aleatorios (aglomerados no jerárquicos)

Todo integrado bajo una arquitectura común y abierta. La fábrica del futuro, como la visualiza el proyecto AUTORECON, abarca las tecnologías que se muestran en la Figura 3.1:

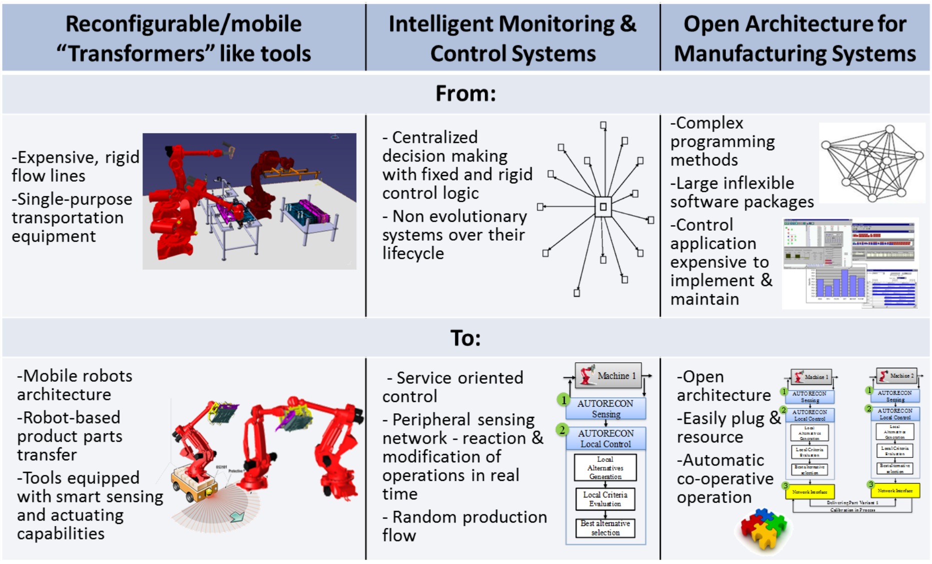

Figura 3.1: Arquitectura AUTORECON

3.3.1.1. Principales contribuciones

Las contribuciones en este proyecto fueron múltiples. Se comenzó con el diseño de un robot móvil capaz de navegar de modo autónomo y preciso por la planta de producción, ya que existían muchas limitaciones de espacio. Para ello, fue necesario diseñar e instalar un sistema dinámico y cinemático con capacidad omnidireccional que puede realizar movimientos concisos en un espacio muy reducido. El robot móvil debía poseer una gran envergadura y capacidad de carga para albergar un manipulador industrial de grandes dimensiones. El objetivo era manipular cargas voluminosas y pesadas. La plataforma móvil debía poseer también un sistema de suspensión neumático que le posibilitase elevarse y bajarse al nivel del suelo para fijarse con el mismo, mediante unos enclavamientos de precisión, ya que existía riesgo de vuelco al albergar un manipulador de grandes dimensiones. A nivel de software se implementaron sistemas de localización y navegación autónoma basada en láser 2D mediante SLAM y el uso de librerías ROS. A su vez se implementó un sistema de percepción mediante cuatro cámaras que monitorizaban unos marcadores situados en el suelo para realizar una aproximación muy precisa con el robot a los enclavamientos del suelo para fijarse al mismo. Está técnica, conocida como *Visual Servoing*, se basa en la corrección de la posición del robot en función de las lecturas de un sensor de percepción, en este caso las cámaras de visión 2D. De ese modo, el robot se posicionaba de modo preciso encima de los enclavamientos y descendía gracias al sistema de suspensión neumática instalada. Este anclaje al suelo permitía además alimentar el manipulador externamente por medio de unas escobillas, ya que dado su elevado consumo no podía alimentarse desde las baterías de la plataforma móvil. En la Figura 3.2 se observa la planta piloto diseñada y creada para la validación de las tecnologías desarrolladas en el proyecto. En ella, se puede ver el manipulador móvil que navega de modo autónomo e interactúa con los demás manipuladores industriales para lograr una producción flexible y dinámica.

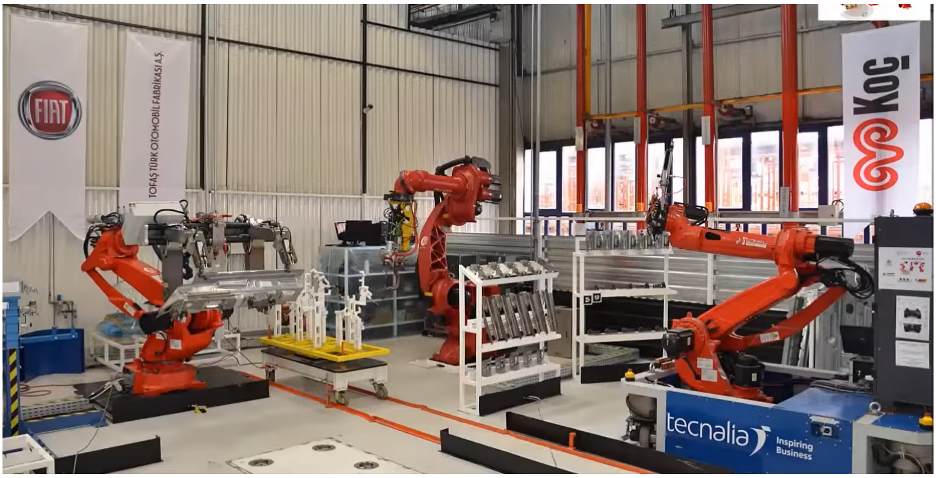

Figura 3.2: Ejecución de la demo en la planta de producción Tofas

3.3.2. Thomas

El proyecto THOMAS [14] (Mobile dual arm robotic workers with embedded cognition for hybrid and dynamically reconfigurable manufacturing systems) tiene como objetivo crear un taller dinámicamente reconfigurable mediante el uso de manipuladores móviles capaces de percibir su entorno y cooperar con otros robots y humanos. Dentro del proyecto se investigó en los siguientes temas:

1. Espacio de trabajo dinámico. Mediante recursos móviles capaces de navegar en el taller mientras utilizan diferentes herramientas.

2. Capacidad de percibir la tarea y el entorno utilizando:

    - Los sensores embarcados en el robot
    - La percepción colaborativa mediante la combinación de sensores de múltiples recursos y sensores del taller.

3. Balanceo de la carga de trabajo redirigiendo los robots a estaciones más ágiles y permitiendo que ajusten automáticamente su comportamiento tomando decisiones.

4. Programación rápida y ejecución automática de múltiples tareas basadas en el concepto de "habilidadesü operaciones atómicas que se pueden combinar en función del entorno percibido para generar automáticamente el programa del robot.

5. Colaboración segura entre humanos y robots eliminando barreras físicas (vallas, etc.) mediante la introducción de capacidades cognitivas que permitan a los robots detectar al humano y sus intenciones.

Los casos de uso donde se aplicaron las tecnologías pertenecían a los sectores de automoción y aeronáutica. Concretamente las tareas que se realizaron fueron las siguientes.

Caso de uso automoción

Tiene como objetivo abordar el impacto del *kitting*[1] en la producción real. La introducción de la distribución tipo *kitting* permitirá a los trabajadores concentrarse en las tareas más productivas, pero, por otro lado, introducirá importantes desafíos técnicos para las operaciones a robotizar.

Este caso de uso se centrará en las tareas de montaje del panel del vehículo y tendrá como objetivo presentar el sistema robotizado móvil demostrando las funcionalidades de montaje:

- Capacidad de percibir, detectar y seguir el panel del vehículo en movimiento mientras es transportado sobre un carro mientras.

- Posibilidad de seleccionar piezas del kit en el carro, utilizando los sistemas de percepción del robot.

- Capacidad para realizar operaciones de montaje (inserción, atornillado, inspección) con precisión.

Estas tareas son aplicables a muchas fábricas de automóviles ya que se trata de tareas de montaje muy utilizadas en el sector. La Figura 3.3 ilustra el proceso de detección, seguimiento y manipulación en movimiento de las piezas propuestas en el caso de uso.

[1] El kitting es un proceso o servicio logístico que consiste principalmente en aunar las diferentes piezas que forman un producto para crear un paquete. Tras reunir todos los materiales del producto en un solo kit, se envía a la siguiente fase del proceso donde los operarios del almacén procederán a su ensamblaje.

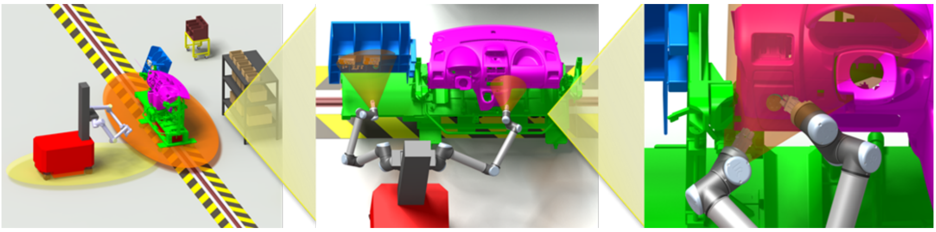

Figura 3.3: Ejecución de las tareas en automoción

Con el propósito de lograr una gran eficiencia en el proceso de montaje de los amortiguadores, la tarea de roscado de ciertos tornillos se ha de realizar en movimiento, mientras los amortiguadores son transportados por un AGV (*Automated Guided Vehicle*) entre células. El AIMM debe seguir al AGV de modo preciso para realizar el proceso de atornillado en ambos amortiguadores, los cuales también deben de ser detectados por el robot. En la Figura 3.4 se observa el AGV que transporta los amortiguadores con un utillaje móvil dedicado para tal fin.

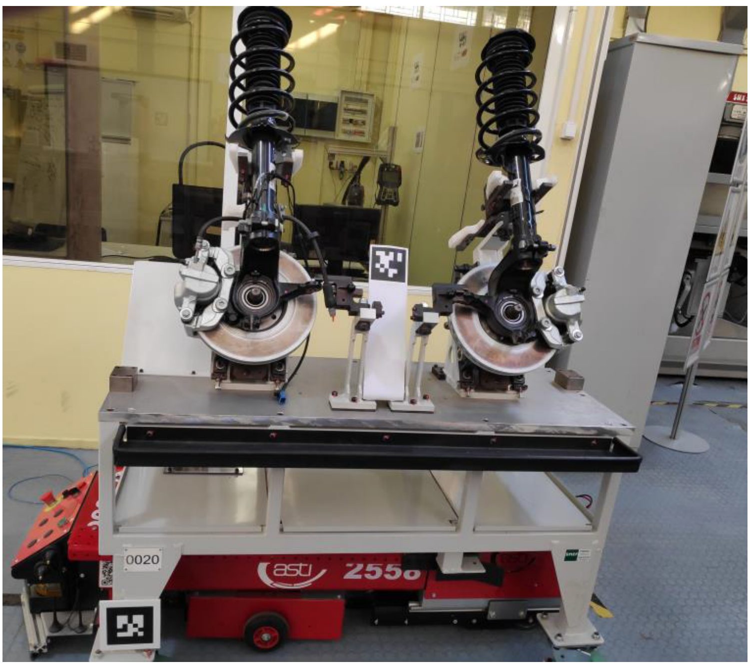

Figura 3.4: AGV transportando los amortiguadores entre células

Caso de uso aeronáutico

El caso de uso aeronáutico se basa la ejecución de tareas de taladrado, inspección de remaches y lijado de pintura de diferentes estructuras aeronáuticas, mediante un AIMM de modo autónomo. Para ello, el robot lleva embarcado un complejo sistema de percepción artificial, entre el que se destaca un sistema dual de cámaras estéreo fijadas en los brazos del robot, como se puede ver en la Figura 3.5

Figura 3.5: Cámaras instaladas en el AIMM del proyecto Thomas

El robot debe ser capaz de navegar de forma autónoma a lo largo de la planta de producción, teniendo en cuenta y evitando los posibles obstáculos para alcanzar su objetivo satisfactoriamente. Tras su llegada, realizará un posicionamiento preciso delante de la plantilla de taladrado que deberá detectarla mediante el sistema de visión incorporado. El algoritmo de posicionamiento preciso se basa en la corrección de la posición del AIMM gracias a un controlador proporcional cuya entrada es la información de posición obtenida mediante la detección de una referencia determinada. Para ello, se rastrea un *ARTag* ubicado en la estación de acoplamiento mediante una cámara RGB monocular montada en la parte frontal del robot como se puede apreciar en la Figura 3.6

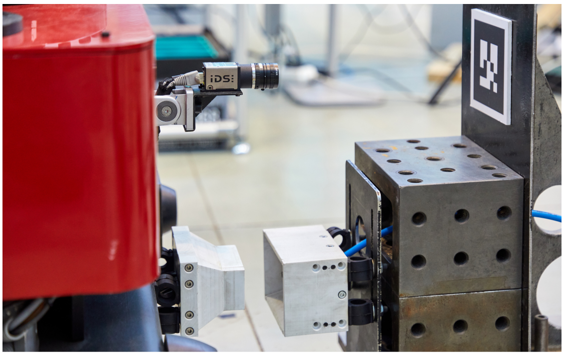

Figura 3.6: Sistema de posicionamiento preciso del AIMM

Tras el posicionamiento preciso del robot delante de la estructura que soporta el ala del avión, este debe ser capaz de detectar las plantillas de perforación fijadas sobre el ala para proceder a su taladrado. Para ello, debe identificar la plantilla en su totalidad mediante una cámara estero de gran campo de visión y, en una segunda instancia, detectar todos los agujeros de la misma utilizando otra cámara estero con mayor precisión, fijada en el otro manipulador. La detección se lleva a cabo mediante el emparejamiento de la información recibida por las cámaras (nube de puntos) y el modelo CAD 3D de la plantilla previamente procesado. En la Figura 3.7 se puede observar la detección de los agujeros en la plantilla real mediante el sistema de percepción artificial basado en técnicas de visión por computador.

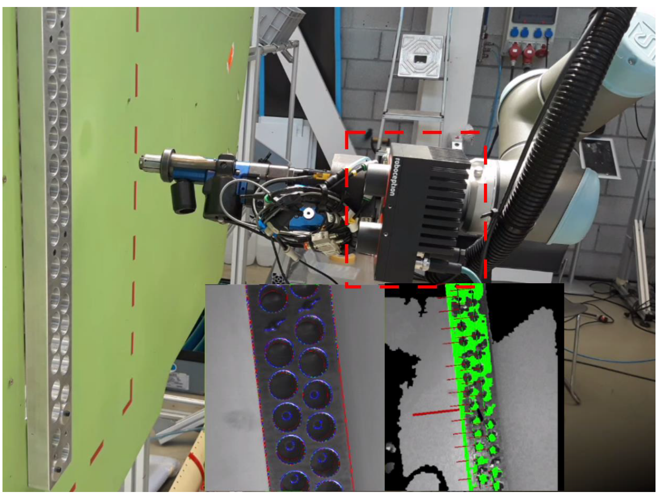

Figura 3.7: Sistema de posicionamiento preciso del AIMM

3.3.2.1. Principales contribuciones

Las contribuciones en este proyecto fueron múltiples, comenzando por el diseño de un novedoso AIMM que pretende dar solución a los requerimientos industriales actuales de los sectores de la aeronáutica y automoción. Se busca un diseño innovador que combine una robusta plataforma móvil con gran versatilidad de movimiento y capacidad de carga junto con dos brazos colaborativos que favorezcan las tareas de manipulación compleja y bimanual. A su vez, se combinan múltiples sensores de diferentes naturalezas para lograr una buena percepción artificial del entorno y por tanto una mayor autonomía del robot, sin olvidar todos los aspectos referentes a la seguridad normativa (directivas, análisis de riesgos, marcado CE) y a la seguridad inherente del robot (sensores con certificación de seguridad, combinación de percepción 2D y 3D, etc.) Se ha logrado una navegación célula a célula robusta para este nuevo robot mediante el ajuste de sus parámetros específicos. A su vez, se ha mejorado la navegación 2D mediante la fusión de información de sensores 3D que permiten detectar obstáculos más allá del plano de el escáner láser, mejorando la seguridad y robustez del sistema. En navegación intracelular se ha desarrollado un módulo basado en ROS de posicionamiento preciso del robot. Se ha utilizado un marcador AR para autolocalizarse con respecto a una posición relativa precalibrada. Además de para localizarse de modo preciso, este sistema se utiliza para suministrar corriente eléctrica y neumática externa al robot. El acoplamiento estático ha demostrado ser robusto y preciso.

El siguiente reto ha consistido en realizar el seguimiento de un carrito tirado por un AGV filoguiado. Este seguimiento es necesario ya que se pretende realizar un proceso de roscado de una pieza transportada por dicho carrito. Por ello, el robot debe realizar un seguimiento muy preciso, imitando al detalle la trayectoria descrita por el mismo. La unión del sistema AGV-carrito no es rígida, por lo que se pueden producir movimientos incontrolados en la parte del carrito, siendo este arbitrario y dependiendo del estado de parada del que partía. Este hecho complica en gran medida el sistema y obliga a pensar en una solución adaptativa para que el robot pueda corregir su trayectoria y adaptarse de modo ágil en todo momento.

En una primera instancia se ha realizado un estudio del estado del arte en detección y seguimiento mediante láser. Trabajos sobre detección de personas y vehículos en calles transitadas [15] han servido de guía, además de técnicas que combinan SLAM con seguimiento de objetos (DTMO) [16]. La detección y el seguimiento se realiza mediante las imágenes obtenidas de la cámara superior del robot y de las lecturas de los láseres 2D. Los primeros ensayos realizados han mostrado que las imágenes de la cámara a esa distancia (1,80 metros) no son lo suficientemente precisas para obtener una posición con los márgenes necesarios para realizar la operación. Es por ello, que se ha instalado una cámara industrial, al igual que para el estacionamiento preciso del robot. Esta cámara de la marca IDS uEye GigE se ha instalado en el lateral del robot dando una imagen mucho más cercana y por lo tanto más precisa del carrito. Se ha colocado un marcador AR en el carrito que debe ser detectado por el sistema a un refresco de imagen de 30 fps.

Para lograr el objetivo de seguimiento preciso se ha implementado un bucle de control con tres PIDs para controlar el error de desplazamiento lineal, lateral y angular. Es necesario realizar un proceso de calibración previo donde se indica la distancia lateral a mantener entre el manipulador móvil y el AGV. Tras ello, el robot sigue de modo preciso al carrito y corrige cualquier movimiento errático del mismo. Con la solución propuesta se consigue una precisión de <1cm cuando el sistema se estabiliza, lo cual tarda alrededor de 2 segundos en los peores casos.

En la Figura 3.8 se observa el AIMM realizando un proceso de seguimiento preciso sobre el carrito tirado por el AGV para ejecutar la tarea de roscado del amortiguador.

Figura 3.8: AIMM siguiendo al carrito tirado por el AGV para realizar tareas de roscado

Además de la solución de seguimiento comentada, se han realizado otras mejoras al sistema de navegación ROS que utilizamos:

- Navegación 2D mejorada con percepción 3D.
- Navegación 3D basada en VisualSLAM [17] [18].
- Capacidad de modificación dinámica de la huella (footprint) del robot para tener en cuenta la disposición de los brazos en todo momento durante la navegación del robot. De ese modo, se asegura que el planificador tiene el cuenta la posición

de los brazos de robot al navegar de modo autónomo y planifica rutas seguras en consecuencia.

- Mejoras a bajo nivel del control cinemático del robot para optimizar su funcionamiento.

Todas estas aportaciones han sido publicadas en el artículo de investigación denominado: *Innovative Mobile Manipulator Solution for Modern Flexible Manufacturing Processes* el cual fue publicado en la revista Sensor correspondiente al segundo cuartil.

3.3.3. Sherlock

Proyecto SHERLOCK [19] (Seamless and safe human - centred robotic applications for novel collaborative workplaces)

Para abordar la creciente necesidad de líneas de fabricación flexibles, el paradigma de fabricación debe avanzar hacia soluciones híbridas, que combinen las capacidades de los humanos y las máquinas. Si bien se presta mucha atención a las mejoras tecnológicas de las soluciones colaborativas entre humanos y robots (HRC), el bienestar psicológico y social del operador sigue siendo un tema que se pasa por alto, lo que genera problemas de rendimiento y aceptación, al lidiar con las aplicaciones y la complejidad. El proyecto SHERLOCK, financiado con fondos europeos, aborda estas deficiencias y aspira a desarrollar aplicaciones robóticas centradas en las personas, flexibles y seguras, para nuevos lugares de trabajo colaborativos. El proyecto introduce nuevas tecnologías robóticas, como robots colaborativos de alta y baja carga útil, exoesqueletos y robots móviles de doble brazo, mejorados con mecatrónica inteligente y conocimiento basado en inteligencia artificial para aumentar las capacidades humanas.

La colaboración entre humanos y robots ha evolucionado para abordar la necesidad de una producción flexible, pero presenta inconvenientes como incapacidad para cubrir todas las aplicaciones, bajo rendimiento en la colaboración y una gran complejidad. SHERLOCK tiene como objetivo introducir las últimas tecnologías robóticas en los entornos de producción, creando estaciones eficientes que están diseñadas para ser seguras y garantizar la aceptación y bienestar de los operadores. Los requisitos de producción actuales impulsan los siguientes objetivos que se tratan en el proyecto. Se resaltan en los que más ha contribuido el autor:

1. Estación de Producción Colaborativa de Soft Robotics [20]: Partiendo de una base de seguridad humana:
    - AURA, un manipulador colaborativo de alta carga útil.
    - Exoesqueletos inteligentes con funcionamiento ajustable.
    - **Manipuladores móviles seguros de doble brazo**.

2. Interacción, colaboración y conciencia centradas en el ser humano mediante el desarrollo de:
   - Interfaces que inspiran confianza/familiaridad, lo que permite una interacción fluida con RR.HH.
   - **Métodos para evaluar el impacto de los sistemas HRC en los usuarios.**
   - Principios/estándares de diseño para mantener la seguridad/bienestar psicológico del operador en HRC
   - Configuraciones de producción para personas con restricciones especiales que explotan la cognición del robot.
3. La técnicas de IA favorecen el aprendizaje de los robots en aplicaciones autónomas: permite a los robots comprender su entorno, razonar sobre él y adaptarse mediante:
   - **Percepción multinivel para la evaluación de procesos y entorno**.
   - Sistemas de monitoreo de espacios de trabajo seguros.
   - **Planificación y coordinación autónoma de tareas de robots humanos**.
   - Aprendizaje interactivo, adaptación al operador y simplificación de la enseñanza de nuevas tareas.

SHERLOCK aplica las tecnologías desarrolladas en diferentes sectores de producción industrial como la máquina herramienta y la aeronáutica.

3.3.3.1. Principales contribuciones

Una de las principales contribuciones que se ha realizado dentro del marco del proyecto Sherlock es el diseño y fabricación de un novedoso manipulador móvil (AIMM). Para ello, se han tenido en cuenta los mayores avances tecnológicos con el fin de responder a las demandas actuales de la industria, bajo los siguientes factores:

Navegación

Al tratarse de un manipulador móvil es imprescindible que la movilidad sea precisa, versátil y robusta. Por ello, gracias a la experiencia obtenida al haber probado otros sistemas motrices como:

- Modelos holonómicos
- Skid steer
- Ackermann y doble ackermann
- Diferenciales con ruedas y con orugas

- Omnidirecionales basados en motorruedas

Se ha decidido instalar un sistema omnidireccional basado en ruedas *mecanum* [21]. Este sistema ofrece la posibilidad de realizar movimientos en traslación y rotación sin necesidad de reconfigurar las ruedas, generando un movimiento continuo.

Percepción

Para percibir el entorno y dotar al robot de una mayor autonomía se han instalado los siguientes sensores:

- Cámara Ueye IDS [22] de gran resolución para implementar nuestra solución de visual docking preciso.
- Láser Sick Micro Scan3 Pro [23]. Son los sensores más novedosos de la marca que aportan información densa y precisa del entorno.
- Sensor inercial (IMU) para complementar la información de odometría proveniente de los datos recogidos por *encoders* instalados en los motores de las ruedas.

Manipulación

Se han seleccionado los nuevos manipuladores colaborativos IIWA [24] del fabricante KUKA ya que poseen sensores de fuerza, impedancia y 7 grados de libertad logrando una gran precisión y repetibilidad. Tras realizar un estudio de alcanzabilidad, se han diseñado unos soportes con pendiente para anclar los brazos al robot y que la suma de los espacios de trabajo sea mayor. Para satisfacer los requerimientos del proyecto Sherlock, en el cual se pretende realizar una comanipulación de largas piezas de fibra de carbono entre un operario y el robot, se han diseñado unos útiles/herramientas que se fijan en la última articulación del robot y que permiten sostener la pieza mediante la utilización de ventosas y vacío neumático.

Seguridad

Debido a que el robot va a trabajar en colaboración con personas, la seguridad es un factor imprescindible y debe ajustarse a la normativa vigente, tanto la norma “EN 1525: seguridad de la carretilla de manutención, carretillas sin operador y sus sistemas” como la nueva UNE EN ISO 3691-4:2020 [25] (versión vigente durante el desarrollo del proyecto y recientemente actualizada a la versión 3691-4:2024).

El sistema láser instalado se complementa con el hardware/software de seguridad FlexiSoft del fabricante Sick, que permite la generación de múltiples zonas de trabajo seguras. Para garantizar la seguridad, el sistema se parametriza teniendo en cuenta una serie de factores como la envergadura, el peso y la velocidad actual del robot. Gracias a este sistema y sus parámetros dedicados, el robot se adapta al medio en función de las lecturas de los láseres pudiendo gestionar la velocidad actual e incluso reducirla hasta detenerse, realizando una parada controlada. Los motores están provistos con frenos mecánicos que se activan en ausencia de corriente o debido a una parada de emergencia. El robot posee 4 botones de parada de emergencia ubicados en su perímetro y, como complemento, se ha instalado un sistema de parada de emergencia remoto/inalámbrico comunicado por ondas de radio.

Elementos adicionales

Teniendo en cuenta las lecciones aprendidas de robots diseñados en el pasado, se han añadido los siguientes elementos adicionales al nuevo robot:

- Sistema neumático de producción de aire comprimido de 20 litros de capacidad
- Sistema para generar vacío con vacuostato programable que ahorra un 90 % de flujo de aire frente a los tradicionales sistemas Venturi.
- Baterías de litio LiFePo4 de gran capacidad con autonomía para 8 horas y sistema inteligente de gestión de consumo BMS.
- Sistema distribuido con redes y subredes autogestionadas.
- Inversor de potencia de 3000W para disponer de corriente alterna.
- Salidas neumáticas y de tensión eléctrica para suministrar recursos a elementos ajenos al robot como garras y herramientas.
- Se ha invertido en la interacción con el humano, instalando una pantalla táctil que aporta información del robot y del proceso. Además, se ha instalado una tira de LED alrededor del perímetro del robot que ilumina cada zona en función del vector velocidad que está ejecutando el robot al navegar. Esto ayuda a entender e interpretar qué está haciendo el robot y a dónde se dirige.
- Conectividad inalámbrica con acceso a Internet.

Con el fin de aumentar y mejorar las capacidades del robot y su interacción con los humanos, el autor ha diseñado y desarrollado un sistema de comunicación mediante comandos de voz (*speech recognition*) utilizando percepción artificial y sistemas basados en redes neuronales como TensorFlow [26]. El robot transcribe a texto la voz recibida por el operario (*speech to text*) y este texto es interpretado de modo semántico, es decir, obtiene información clave dentro del contexto de la conversación. Tras ello, el robot realiza las acciones encomendadas (navegar a una zona, guardar un punto de interés, indicar su estado actual, etc.) mientras va aportando información al operario mediante voz (*text to speech*).

En la Figura 3.9 se puede observar el robot resultante de la investigación realizada en este proyecto. El robot se ha llamado Robouton como guiño al codiseñador del mismo.

Figura 3.9: Robot Robouton diseñado y fabricado dentro del marco del proyecto Sherlock

3.3.4. Cleandem

Proyecto Cleandem [27] (Cyber physicaL Equipment for unmAnned Nuclear DEcommissioning Measurements).

El mercado europeo de desmantelamiento, también conocido por sus siglas en inglés *decommissioning and dismantling* (D&D), de instalaciones nucleares se caracteriza por su gran crecimiento. El proyecto Cleandem, financiado con fondos europeos, desarrolla un avance tecnológico para las operaciones de D&D que ahorrará tiempo, reducirá costes y minimizará la intervención humana a la vez que aumentará la seguridad. Con la colaboración de once socios de cuatro países de la Unión Europea, el proyecto desarrolla un sistema ciberfísico utilizando un vehículo terrestre no tripulado equipado con innovadores sensores de detección radiológica. Llevará a cabo una evaluación radiológica del área y monitoreará las operaciones de D&D. Esto dará como resultado un gemelo digital 3D completamente detallado del área investigada, ampliado con información radiológica.

El objetivo del proyecto es desarrollar un sistema ciberfísico que respalde las operaciones de los usuarios finales, realizando inicialmente una evaluación radiológica del área y luego monitoreando las operaciones de D&D durante la caracterización final de la planta. El gemelo digital resultante ampliado con información radiológica proporcionada por los sensores embarcados en el robot permitirá una planificación eficiente y eficaz de las acciones de desmantelamiento y optimizará la clasificación de los residuos nucleares para su reprocesamiento o su entrega al almacenamiento final. Los objetivos del robot móvil son lo siguientes: ahorrar tiempo, reducir drásticamente los costos, minimizar la intervención humana, mejorar la seguridad de los trabajadores y ser más ecológicos. Los resultados del proyecto se evalúan y validan en una extensa campaña de pruebas. Estás se realizan en laboratorios, en entornos simulados y finalmente en una ubicación con restos nucleares reales.

3.3.4.1. Principales contribuciones

Este proyecto surge de la necesidad de monitorización y desmantelamiento de zonas con restos nucleares ya que son tareas altamente peligrosas para el ser humano debido a los efectos de la radiación y a la posible contaminación del entorno, por ejemplo en partículas suspendidas en el aire. Para afrontar este problema se requiere del diseño y fabricación de un AIMM con ciertas características y capacidades para hacer frente a este tipo de situaciones. Como se puede observar en la Figura 3.10 el sistema se basa en un AIMM compuesto por una base móvil, un brazo robótico y una serie de sensores de percepción artificial.

Figura 3.10: AIMM diseñado y fabricado dentro del marco del proyecto Cleandem

Diseño del robot

Este proyecto se caracteriza por la necesidad de monitorizar y desmantelar residuos en zonas de difícil acceso dentro de entornos no estructurados. Por ello, el autor ha realizado un estudio sobre las necesidades que la cinemática y el sistemas de tracción han de cumplir. El robot debe desplazarse por entornos tanto de interior como de exterior enfrentándose a diferentes tipos de pavimentos, zonas irregulares, desniveles, rampas, etc. Además debe ser capaz de realizar movimientos precisos en lugares poco accesibles y sin grandes opciones de maniobrabilidad. Con toda esta información como precondición se ha decido adquirir un sistema omnidireccional basado en motoruedas. Este sistema que combina ocho motores, cuatro de tracción y cuatro de rotación permite realizar movimientos precisos en todas las direcciones del plano, además de ser capaz de sortear las dificultades del terreno ya que se han elegido ruedas de goma multitaco.

El diseño del robot móvil ha tenido en cuenta la reducción de contaminación por contacto. La carcasa del robot está diseñada específicamente teniendo en cuenta el problema de la exposición al polvo contaminado. Por ello, se han priorizado las superficies lisas, evitando zonas donde se pueda acumular polvo, facilitando la limpieza. El robot dispone de ventilación para enfriar los componentes eléctricos internos. Estas aberturas al exterior están debidamente selladas con filtros HEPA.

El sistema se combina con un manipulador UR5 con seis grados de libertad y 5Kg de capacidad de carga situado en uno de los extremos del robot para lograr el mayor alcance posible. Posee una garra multipropósito con el fin de recoger muestras del entorno en caso de ser necesario. Además se han diseñado interfaces mecánicas para fijar los diferentes sensores nucleares en el brazo en sustitución de la garra.

Comunicaciones y Telepresencia

Debido a que el AIMM debe ser teleoperado en determinadas ocasiones, se ha instalado un potente sistema inalámbrico punto a punto Wi-Fi. El robot dispone de múltiples antenas de comunicación que transmiten información con baja latencia sobre el estado del robot, las imágenes de las cámaras instaladas, las lecturas de los láseres y la recepción de las órdenes de movimiento desde la estación de control. La telepresencia, que se define como el conjunto de tecnologías que permiten a una persona sentirse como si estuviera presente en un lugar distinto a su verdadera ubicación, es de vital importancia en este tipo de aplicaciones ya que, en ciertas ocasiones, el robot será teleoperado por un operario. Cuanta más información del entorno pueda proveer el sistema y ser representada en una interfaz gráfica de usuario, más sencilla y con mayor probabilidad de éxito se realizará la tarea de teleoperación. Para ello, se han embarcado en el robot una serie de sensores de percepción artificial.

Sensores

El robot puede llevar embarcado diferentes sensores nucleares gracias a las interfaces mecánicas que se han diseñado ex profeso. Con ellos, el AIMM es capaz de monitorizar, tomar muestras y medir la radiación de los restos nucleares. Además de la sensórica nuclear mencionada, el robot necesita embarcar sensores de diferente naturaleza para lograr percibir su entorno con la mayor fidelidad posible.

El robot se ha equipado con láseres 2D que proveen información topológica del terreno. Estos láseres se usan tradicionalemnte para la creación de los mapas donde el robot se va a ubicar. Esta información se representa en forma de mapa digital basado en escala de grises, los cuales el robot interpreta para ubicarse, evitar obstáculos y generar trayectorias libres de colisión. Sin embargo, el campo de visión de este tipo de sensores es limitado ya que las lecturas se basan en un solo plano. Esto es peligroso ya que todo lo que se sitúe por encima o debajo de dicho plano es invisible para el robot. Para solventar este inconveniente, se ha instalado un sensor con tecnología LiDAR 3D. Gracias a este sensor, el robot realiza una reconstrucción volumétrica del entorno por el que navega creando un mapa en 3 dimensiones mediante la unión de las nubes de puntos obtenidas. Esta información es mucho más valiosa que la suministrada por el LiDAR 2D y será utilizada para localizarse y evitar obstáculos en el mapa 3D generado.

Con el fin de obtener una odometría más precisa, la información de los codificadores instalados en los motores de las ruedas se combina con un sensor IMU (Unidad de Medición Inercial) que combina acelerómetro, giroscopio y magnetómetro. El IMU proporciona información sobre las aceleraciones y rotaciones que realiza el robot mejorando la odometría ya que es invariante al deslizamiento y derrape de las ruedas.

Para los tramos en los que el robot navega en zonas de exterior al aire libre se ha instalado un dispositivo GNSS, el cual proporciona información de geolocalización para determinar la ubicación precisa del receptor.

Para dar soporte a la teleoperación se han instalado 2 cámaras RGBD para que el teleoperador pueda observar el entorno desde el puesto de control. Además, la información de estas cámaras también se puede utilizar para evitar obstáculos durante la navegación autónoma.

Navegación 3D

Uno de los objetivos clave del proyecto CLEANDEM es mejorar la precisión y repetibilidad de las mediciones de los restos nucleares. Las técnicas de localización 2D actuales son maduras y robustas, pero su precisión está acotada por el ruido de los sensores y la representación limitada del entorno. Se puede obtener una gran precisión mediante técnicas tradicionales de localización 2D, pero generalmente requieren de mapas altamente precisos y/o la instalación de marcadores artificiales colocados en el entorno. La naturaleza de los casos de uso propuestos en el proyecto CLEANDEM hace difícil utilizar esos enfoques, ya que el tiempo de exposición debe reducirse lo máximo posible, lo que dificulta grabar mapas altamente detallados o colocar marcadores artificiales en el entorno. Además, las técnicas de localización 2D no son adecuadas para operaciones al aire libre y se requiere su utilización tanto en escenarios interiores como exteriores.

El proyecto busca mejorar la precisión de la localización en interiores y permitir que el robot navegue de forma autónoma al aire libre, por lo que se ha migrado de un sistema de localización y navegación en 2D a uno en 3D.

La representación 3D del entorno es mucho más rica en información y permitirá una mejor precisión de localización con mapas de calidad inferior, creados rápidamente, y una localización exitosa en entornos más grandes y sin características distintivas, típicos de escenarios al aire libre. Actualmente no existe una suite de navegación 3D "estándar" disponible en ROS que cubra todos los aspectos requeridos de la navegación (mapeo, localización y planificación). Por lo tanto, el objetivo en el proyecto es compilar una suite de navegación 3D combinando diferentes módulos en una solución de navegación 3D completa. Dado que no se define ningún estándar, los mapas 3D se almacenan en el formato PCD (Point Cloud Library) que es compatible con la mayoría de los sistemas operativos comúnmente utilizados: Linux, Windows, MacOS y Android. PCL está completamente integrado en ROS y es compatible con otros archivos de datos de nube de puntos 3D (*.stl, *.obj y *.x3d). Los archivos PCD pueden almacenar y procesar conjuntos de datos de nube de puntos organizados y generar histogramas n-dimensionales para descripciones de características, ambos realmente importantes para aplicaciones en tiempo real y visión por computadora, así como para un modelo digital funcional.

Módulo de Mapeo

El proceso de mapeo se realiza utilizando la biblioteca LIO-SAM [28]. LIO-SAM es una biblioteca de generación de odometría basada en sensores LIDAR e IMU. El movimiento del sensor se estima con precisión combinando la coincidencia de nubes de puntos con la medición inercial. La coincidencia de nubes de puntos se realiza contra una representación 3D creada a partir de puntos invariantes detectados en las nubes de puntos. Esta representación 3D es lo suficientemente densa como para ser utilizada como un mapa 3D para una navegación posterior (Figura 3.11).

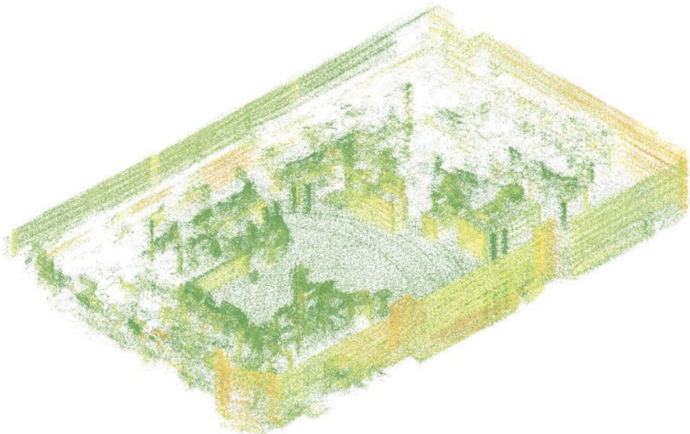

Figura 3.11: Muestra de un mapa 3D generado por LIO-SAM (el techo ha sido eliminado para visualización)

Módulo de Localización

Para la localización, se ha incorporado a la suite la biblioteca de localización HDL_ localization [29]. La localización realizada por esta biblioteca se basa en una variante del método de coincidencia de nubes de puntos de la Transformada de Distribución Normal (NDT) contra un mapa global. El sistema realiza un seguimiento de la posición estimada utilizando un Filtro de Kalman no lineal. En cada paso, la pose estimada se actualiza utilizando la medición inercial y luego se refina utilizando el método NDT mencionado. En la Figura 3.12 se puede observar cómo el robot se localiza en el mapa.

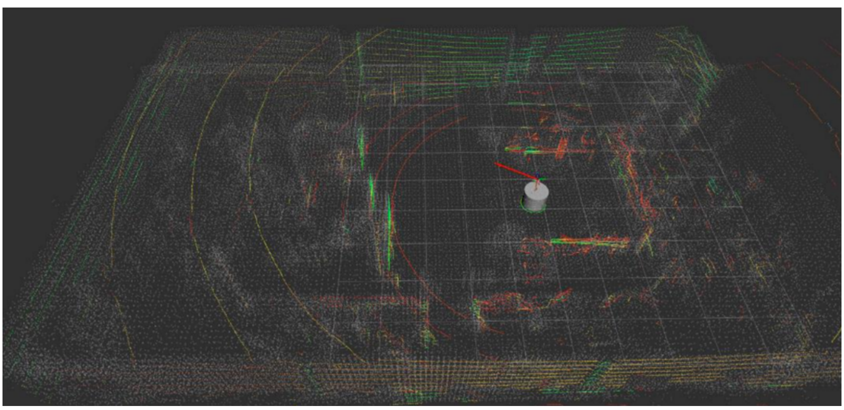

Figura 3.12: Localización basada en HDL sobre un mapa 3D generado mediante LIO-SAM

Modulo de planificación

La parte de planificación de la suite está compuesta por una combinación de módulos que generan una representación 2.5D o pseudo 3D del entorno a partir del mapa 3D (Figura 3.13). Esta representación 2.5D, también conocida como mapa de cuadrícula o mapa de elevación, se utiliza para estimar el espacio transitable del entorno, es decir, las partes del entorno a las que el robot puede llegar por sus propios medios. La representación 2.5D se logra utilizando el módulo *grid_map* [30]. *Grid_map* se utiliza para crear una estimación de la superficie del suelo donde cada celda de la cuadrícula almacena su elevación. La representación de *grid_map* es multicapa, lo que permite almacenar otra información útil calculada a partir del mapa 3D o de *grid_map* mismo.

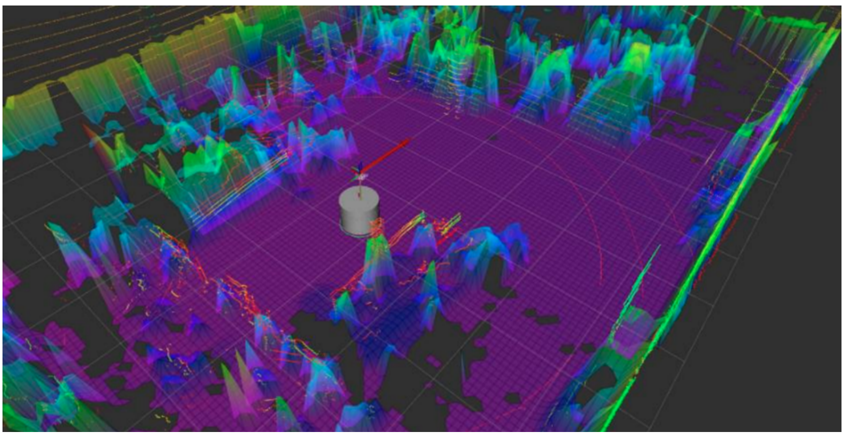

Figura 3.13: Mapa de elevación 2.5D (grid_map) obtenido a partir del mapa 3D

A partir de la información almacenada en grid_map, se calcula el espacio de transitabilidad como una función de la pendiente y la rugosidad del terreno alrededor de cada celda del mapa (Figura 3.13). Esta información de transitabilidad se almacena como un *costmap 2D* directamente utilizable por el *stack* de navegación estándar de ROS (Figura 3.14). La planificación de la ruta real y el control se realizan directamente utilizando los módulos de navegación 2D del *stack* de navegación de ROS (navfn y teb_local_planner).

Figura 3.14: Mapa de transitabilidad 2D obtenido a partir del mapa de elevación

Limitaciones

La solución puede navegar de modo robusto y preciso tanto en entornos de interior como de exterior. Sin embargo, la representación 2.5D impone algunas limitaciones en las capacidades de planificación y navegación que se enumeran a continuación:

- Planificación en múltiples superficies solapadas: Mientras que la localización completa en 3D no tiene ningún problema con entornos complejos, la representación 2.5D para la planificación no puede representar escenarios de múltiples niveles con zonas de planificación superpuestas.
- Dependencia del modelado del suelo: El cálculo del mapa de transitabilidad depende en gran medida de la calidad de la representación del suelo en el mapa 3D. Esto puede suponer un problema en espacios pequeños o abarrotados, ya que los sensores suelen ser sistemas basados en múltiples planos que capturan características verticales del entorno. Los suelos y techos solo se miden de forma dispersa, generalmente desde largas distancias. El modelado adecuado del suelo requiere el montaje inclinado de los sensores, lo que afecta la robustez de la localización.
- Representación 2D de obstáculos: La representación actual de los obstáculos es la proyección en el mapa de transitabilidad de los objetos 3D detectados por el LIDAR. Este enfoque es el más estricto, por lo que aunque es el más seguro, puede limitar la movilidad del vehículo al no considerar la forma completa en 3D de los obstáculos.

3.4. Otros Proyectos

3.4.1. BotaRobota

La necesidad de desinfectar espacios públicos y privados se ha vuelto una prioridad en el contexto de la pandemia de COVID-19. Colegios, hospitales, residencias de mayores y otros lugares con alto volumen de personas requieren una limpieza minuciosa para prevenir la propagación del virus. Sin embargo, las técnicas de desinfección convencionales pueden implicar riesgos para la salud de los trabajadores encargados de llevarlas a cabo. Aquí es donde entra en juego el potencial de la robótica.

Los avances en la industria de la robótica han generado una amplia gama de aplicaciones en diversos campos, y su capacidad para operar de manera autónoma es especialmente relevante en situaciones de riesgo como esta. Los robots pueden desempeñar tareas de desinfección de manera eficiente y sin exponer a los humanos a productos químicos peligrosos. Sin embargo, aún enfrentan desafíos importantes, como la habilidad para abrir puertas.

La capacidad de abrir puertas de forma autónoma es crucial para que un robot móvil pueda desplazarse libremente por un espacio y llevar a cabo una desinfección completa. Este es un problema complejo que requiere soluciones innovadoras en el campo de la percepción artificial. La detección precisa de las puertas, la manipulación segura de las manillas y la navegación autónoma en entornos dinámicos son aspectos clave que deben abordarse.

3.4.1.1. Principales contribuciones

El trabajo realizado propone una solución a este desafío mediante la aplicación de técnicas avanzadas de percepción artificial. Estas técnicas permiten al robot detectar y reconocer puertas, planificar rutas seguras para atravesarlas y manipular las manillas de manera efectiva. Este enfoque representa un paso importante hacia la implementación de robots móviles para tareas de desinfección en entornos reales, contribuyendo así a combatir la propagación de enfermedades infecciosas de manera segura y eficiente.

Navegación

La principal fortaleza de los AIMM en comparación con los manipuladores tradicionales es su capacidad de desplazarse de manera autónoma por su entorno. En esta aplicación, se han contemplado dos niveles distintos de navegación: en primer lugar, una navegación autónoma más general, donde el robot se desplaza entre puntos de interés. Esto es especialmente útil cuando navega a través de distintas áreas o habitaciones (navegación global). En segundo lugar, se ha utilizado una navegación de alta precisión, donde el robot se posiciona con gran exactitud frente a un objetivo específico. Este nivel de precisión es crucial cuando el robot alcanza una puerta que necesita abrir, requiriendo una posición precisa para llevar a cabo con éxito las tareas de percepción y manipulación de la manilla (navegación precisa).

Percepción y manipulación de la manija

Se utiliza el método iterativo RANSAC para detectar la puerta a partir de la nube de puntos del robot. Se segmenta el espacio para evitar confusiones con las paredes y se identifica un clúster que probablemente sea la manija de la puerta. Luego, se estima la posición y orientación de la manija refinando el clúster basándose en diferencias de color con la puerta. Sin embargo, debido al ruido en la nube de puntos, se proyectan los puntos en planos paralelos a la puerta para corregir posibles desviaciones en la orientación.

Se utiliza el enfoque de aprendizaje por demostración para enseñar al robot cómo abrir puertas, permitiendo a usuarios expertos o novatos guiar al robot en los movimientos necesarios. La aplicación consta de módulos para adquirir datos de posición, analizar y filtrar trayectorias, ejecutarlas y proporcionar una interfaz de usuario intuitiva. La tarea de apertura de puertas se divide en cuatro fases para facilitar el aprendizaje y evitar errores: sujeción de manija, giro de manija y apertura inicial de la puerta, apertura amplia de la puerta e impulso final.

La Figura 3.15 muestra el flujo de ejecución de la tarea completa.

Figura 3.15: Flujo de ejecución de tareas para apertura de puertas

3.4.2. ELIKA

Los robots son uno de los principales actores de lo que se conoce como la cuarta revolución industrial o "Industria 4.0". Están transformando los procesos productivos y los entornos en los que las empresas compiten. Su presencia es fundamental en diversos sectores industriales, como la industria automotriz, aeroespacial y farmacéutica, entre otros, ya que se han convertido en una herramienta esencial en los procesos de fabricación. Esta tendencia hacia la robotización está llegando al sector de la alimentación, de forma que, en las plantas procesadoras y envasadoras, es cada vez más habitual ver un robot industrial realizando cierto tipo de tareas. Si bien la incorporación de la robótica ha comenzado por ciertos procesos repetitivos, es de esperar (al igual que sucedió en otras industrias), que se extienda a otro tipo de tareas no tan repetitivas, en las que el retorno económico o la posibilidad de que exista una disponibilidad de tipo 24/7 sea relevante. Una de estas tareas es la operación de "cocinado de alimentos". En este ámbito, ya se percibe que tecnologías como la robótica o el IoT revolucionarán la industria alimentaria, facilitando la preparación, expedición y recepción de alimentos y cambiando la forma en que la comida llega al usuario final donde, además, las plataformas digitales favorecerán la conexión directa entre pequeños productores y consumidores.

3.4.2.1. Principales contribuciones

Este proyecto supone un reto tecnológico ya que se trata de un sistema novedoso que agrupa diferentes tecnologías en una misma célula autónoma de cocinado de alimentos. La solución se compone de varias máquinas mecatrónicas diseñadas por el autor junto al departamento de ingeniería mecánica que dan servicio a las diferentes acciones requeridas. A su vez se ha instalado un brazo robótico colaborativo con el fin de manipular los productos alimenticios entre las zonas de la célula para su correcto cocinado y entrega. En la Figura 3.16 se muestra el diseño de la célula.

Figura 3.16: Diseño de célula de preparado y entrega de alimentos

La contribución más relevante en este proyecto corresponde con la solicitud de una patente para proteger los nuevos diseños, conceptos y novedosas máquinas dedicadas que componen la célula.

PATENTE Nº: P232555EP

GOBIERNO DE ESPAÑA
MINISTERIO DE INDUSTRIA, COMERCIO Y TURISMO
Oficina Española de Patentes y Marcas

Acknowledgement of receipt

We hereby acknowledge receipt of your request for grant of a European patent as follows:

Submission number	300515362
Application number	EP24382202.0
File No. to be used for priority declarations	EP24382202
Date of receipt	23 February 2024
Your reference	P232555EP
Applicant	FUNDACION TECNALIA RESEARCH & INNOVATION
Country	ES
Title	SYSTEMS AND METHODS FOR HEATING FOOD AND OPENING A BAG

Form 1002 - 1: Public inventor(s)

Designation of inventor

User reference: P232555EP
Application No:

Public

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	The applicant has acquired the right to the European patent:	As employer

Figura 3.17: Solicitud de Patente de sistema Elika

Nuevo paradigma: Industria 4.0 y robótica autónoma 4

4.1. Introducción

La última década ha estado marcada por una serie de avances tecnológicos, cambios en los modelos de negocio y transformaciones en la sociedad en general que han producido una transición hacía una industria moderna y conectada. Esta transición marca un hito crucial en el panorama económico y tecnológico global, representando una evolución fundamental en la manera en que concebimos y llevamos a cabo la producción, la gestión y la interconexión de procesos industriales. Este cambio revolucionario se caracteriza por la convergencia de tecnologías avanzadas, como la inteligencia artificial, el Internet de las Cosas (IoT), la robótica y la analítica de datos, dando lugar a un entorno industrial altamente conectado e inteligente, incorporando tecnologías emergentes y conectando de manera más estrecha el mundo físico con el digital. Esta transición ha dado lugar a cambios profundos en la forma en que vivimos, trabajamos y nos relacionamos con la tecnología.

4.2. Industria 4.0

La expresión Industria 4.0 [31] fue acuñada en Alemania como parte de la iniciativa que busca promover la digitalización y la conectividad en la fabricación. Este enfoque busca mejorar la eficiencia, la flexibilidad y la adaptabilidad de las cadenas de producción, así como facilitar la toma de decisiones basada en datos en tiempo real. Es un concepto que se refiere a la cuarta revolución industrial, caracterizada por la integración de tecnologías avanzadas en los procesos de manufactura y producción. Esta revolución implica la convergencia de sistemas físicos, digitales y biológicos, aprovechando tecnologías como el Internet de las cosas (IoT)[32], la inteligencia artificial (IA)[33], la analítica de datos[34], la robótica avanzada y la realidad aumentada[35], entre otras.

Trabajos como los de Da Xu [36] y Okano[37] hablan de los beneficios de la conexión de dispositivos y sensores en tiempo real a lo largo de la cadena de producción con el fin de monitorizar y optimizar los procesos de fabricación. Por su parte, trabajos como el de Jan [38] analizan diferentes soluciones basadas en IA dentro de un contexto industrial. De este análisis concluyen que, aunque los problemas a menudo son comunes entre diferentes industrias, las soluciones adoptadas frecuentemente son específicas de un sector industrial en particular. No obstante, la tendencia actual es aplicar soluciones generales y adaptarlas a cada contexto.

4.3. Robótica autónoma y flexible

La robótica autónoma y flexible ha emergido como un componente central en la transformación de la industria, proporcionando soluciones innovadoras para mejorar la eficiencia, la adaptabilidad y la capacidad de respuesta en entornos industriales dinámicos. Este enfoque revolucionario implica la implementación de robots capaces de realizar tareas variadas, adaptarse a cambios en el entorno de trabajo y tomar decisiones de manera autónoma. Como expone Goel [39], la robótica tiene un papel fundamental en esta cuarta revolución industrial, asistiendo a los procesos productivos gracias a su versatilidad y capacidad de adaptación. La nueva robótica es capaz de completar tareas de manera inteligente, centrándose en la seguridad, la flexibilidad, la versatilidad y la colaboración. Esta nueva robótica colaborativa en la que los robots comparten el espacio de trabajo y cooperan con los operarios sin necesidad de barreras o delimitaciones físicas, se ha vuelto más económica, productiva y abre muchas nuevas aplicaciones posibles [40]. Su integración en la industria representa un paso significativo hacia la creación de entornos de trabajo más ágiles, eficientes y seguros. A medida que estas tecnologías continúan evolucionando, se espera que desempeñen un papel fundamental en la redefinición de la forma en que concebimos y llevamos a cabo la producción industrial en la actualidad.

4.3.1. AIMM

Una nueva tendencia en la robótica moderna, con aplicación directa en la industria, se basa en la combinación de robots móviles sensorizados con manipuladores antropomórficos. Su fin es satisfacer el mayor número de aplicaciones posible y lograr una gran versatilidad. Los manipuladores móviles industriales autónomos (AIMM, por sus siglas en inglés) son sistemas robóticos avanzados que combinan la capacidad de movimiento autónomo de los robots móviles con la capacidad de manipulación de los brazos robóticos industriales. Estos robots son capaces de operar en entornos industriales complejos, interactuar con su entorno y llevar a cabo tareas de manipulación con precisión y eficiencia. En la Figura 4.1, se puede observar uno de los AIMM que ha sido codiseñado por el autor.

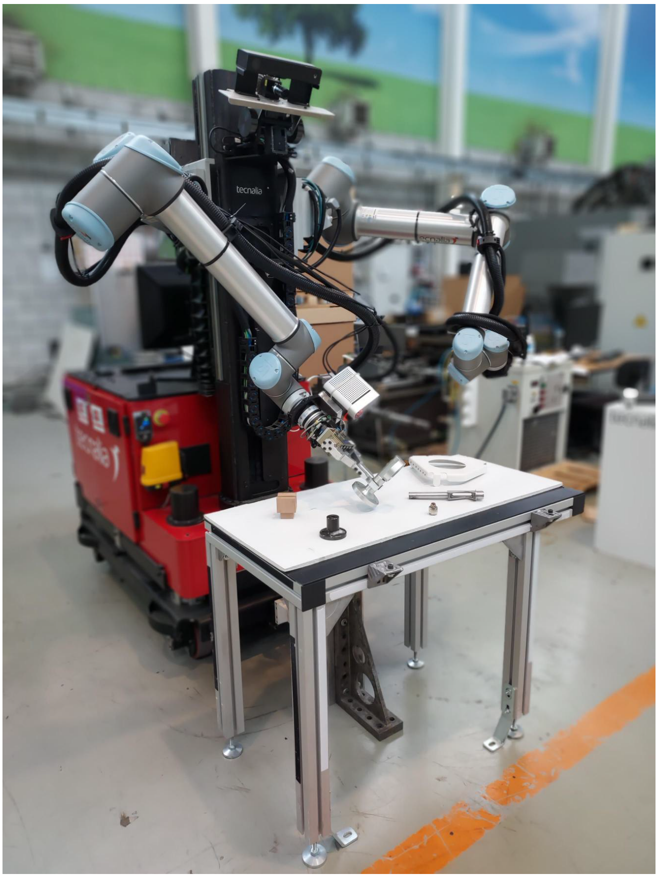

Figura 4.1: AIMM codiseñado por el autor

En los últimos años, ha habido un creciente interés en la investigación y desarrollo de los AIMMs [41], impulsado por la necesidad de automatizar las operaciones en la industria manufacturera y logística con el fin de mejorar la eficiencia y la seguridad en el trabajo. El avance en áreas como la visión por computador, la planificación de trayectorias, la navegación autónoma y la robótica colaborativa ha permitido el desarrollo de novedosos AIMM con capacidades cada vez más sofisticadas [10].

Los AIMMs se emplean en entornos donde, en muchas ocasiones, comparten espacio e interactúan con operarios humanos, por lo que la seguridad y la capacidad de colaboración son fundamentales. Para ello, se han desarrollado herramientas que lo posibilitan basadas en la detección de la presencia humana, la predicción de sus movimientos, la comprensión de sus intenciones y la adaptación del comportamiento del robot para colaborar de modo efectivo. Para lograr este objetivo existen muchas aproximaciones basadas en técnicas de *deep learning* como se puede observar en la síntesis realizada por Zheng [42], donde se comparan 260 artículos de investigación desde 2014. Este estudio proporciona una revisión exhaustiva de las soluciones recientes basadas en el aprendizaje profundo para la estimación de poses en 2D y 3D mediante un análisis sistemático, así como una comparación de estas soluciones en función de sus datos de entrada y procedimientos de inferencia.

La comunicación y la conectividad juegan un papel muy importante en la interacción con estos robots. Siguiendo la estela de la cuarta revolución industrial, donde todo está conectado y surgen nuevos términos como el internet de las cosas o IoT, estos novedosos robots están en completa conexión con sistemas de control y gestión, así como con otros robots y dispositivos con los que comparten datos en tiempo real dentro de los entornos de producción. Esto permite la coordinación y sincronización de las operaciones entre los robots, optimizando la eficiencia y la productividad. En [43] se estudian las oportunidades tecnológicas más destacadas para la facilitación holística de fábricas inteligentes multirobot conectadas en una red inalámbrica. Por si esto fuera poco, los AIMMs se pueden comunicar con los operarios humanos mediantes diferentes señales sonoras, visuales, kinestésicas o mediante sistemas *wearables*. En [44] se revisan las aplicaciones más relevantes de interacción humano-robot.

En términos de aplicaciones, los AIMM se orientan hacia muchos sectores industriales, siendo los más relevantes la industria automotriz, aeronáutica, electrónica, logística, farmacéutica, manufacturera, entre otras [4]. En la industria automotriz, los AIMM pueden ser utilizados para la manipulación y ensamblaje de componentes en la línea de producción, lo que mejora la eficiencia de la producción. En la industria electrónica, pueden ser utilizados para manipular las placas de circuito impreso, ensamblar productos electrónicos y realizar pruebas de calidad. En la logística, pueden ser utilizados para la carga y descarga de mercancías, optimizando los procesos y reduciendo los tiempos de espera. Como se muestra en el trabajo realizado por Neitmann [45], utilizan un AIMM para ensamblar los *flaps* de un avión de modo preciso mediante navegación autónoma y sistemas de impedancia en la manipulación.

Debido a la creciente autonomía de los AIMM, surge la necesidad de abordar cuestiones éticas y regulatorias, por lo que se están desarrollando estándares y regulaciones para garantizar la seguridad y privacidad en la implementación de los robots en entornos industriales. La norma europea más reciente en este ámbito es la UNE-EN ISO 3691-4:2024 [46], que regula los requisitos de seguridad y verificación de las carretillas industriales sin conductor y sus sistemas.

No obstante, a pesar de los grandes avances en el campo de los AIMM, todavía existen desafíos a superar. Algunos de los más destacados incluyen la seguridad, la adaptabilidad a diferentes entornos y tareas, la eficiencia energética, la escalabilidad y la rentabilidad.

La seguridad es un aspecto crucial en la interacción entre el robot, su entorno y los operarios humanos. Así, la detección y prevención de colisiones mediante sensores avanzados, algoritmos de percepción y planificación segura de movimientos son algunas de las habilidades más críticas que los AIMM deben poseer. La adaptabilidad a diferentes entornos y tareas es importante para garantizar la capacidad de operar en una amplia gama de aplicaciones industriales y adaptarse a cambios en los requisitos de producción. La eficiencia energética es un desafío importante, ya que los AIMM deben ser capaces de operar durante largos períodos de tiempo sin tener un impacto significativo en los costos operativos ni interrumpir las operaciones. Respecto a la escalabilidad es necesario que estos sistemas dispongan de arquitecturas modulares y flexibles que puedan ser configuradas y personalizadas para diferentes aplicaciones, además de permitir la coordinación entre múltiples AIMM para mejorar la eficiencia gracias a la producción en equipo. Por último, la rentabilidad también es un gran desafío, ya que los AIMM, a pesar de su elevado coste, deben ser económicamente viables. Por ello, se están investigando [47] modelos de negocio innovadores, como el alquiler y la compartición de AIMM para lograr que su adopción sea más accesible y rentable para las empresas.

En definitiva, los AIMM representan una nueva generación de robots autónomos industriales que combinan la movilidad autónoma con la manipulación industrial, que se caracterizan por su versatilidad y gran capacidad para realizar diferentes tareas de modo autónomo a lo largo de la planta de producción. Gracias a las potenciales ventajas que pueden aportar, se espera que los AIMM sigan evolucionando y desempeñen un papel importante en la industria manufacturera y logística del futuro, lo que conlleva a una continua investigación y desarrollo en el campo.

4.3.2. Navegación autónoma

La navegación autónoma es un campo en constante evolución dentro del mundo de la robótica ya que implica el uso de múltiples tecnologías y técnicas para permitir que un robot se mueva de forma segura y eficiente en un entorno desconocido. Para ello, se requiere un gran nivel de percepción artificial el cual se obtiene empleando diferentes sensores para percibir su entorno, como cámaras, LiDAR (*Light Detection and Ranging*), sónar, etc. Gracias a su utilización, el robot es capaz de detectar objetos en su entorno, medir distancias y crear mapas del entorno en tiempo real. El ciclo de navegación autónoma se basa en cinco fases: percepción, mapeo, localización, planificación y control de trayectorias. En la Figura 4.2, se observa la representación de las fases de navegación autónoma.

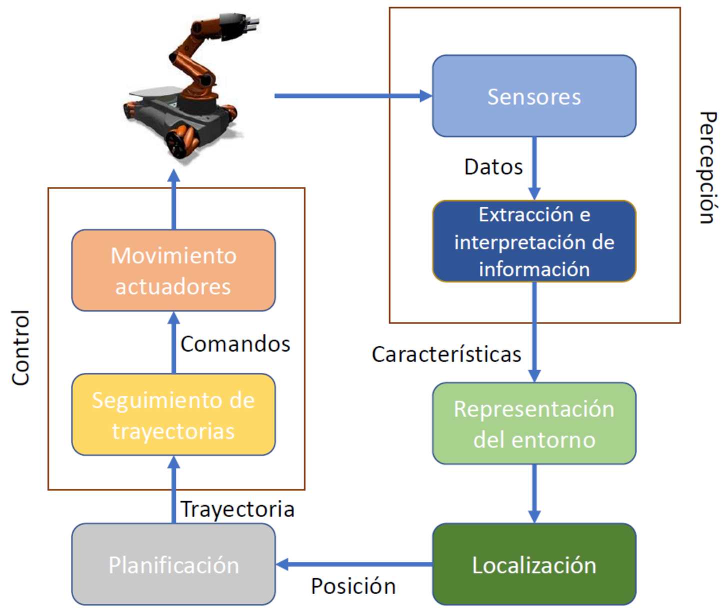

Figura 4.2: Ciclo de la Navegación Autónoma

Percepción - Sensórica

Los sensores juegan un papel fundamental en la percepción artificial del robot y en cómo este entiende e interpreta su entorno. Estos sensores permiten al robot obtener información sobre su entorno circundante, identificar objetos, obstáculos y construir representaciones precisas del espacio en el que se encuentra. A continuación se enumeran los sensores más utilizados en robótica móvil para percepción artificial y mapeado:

- Lidar (*Light Detection and Ranging*): son sensores que utilizan pulsos láser para medir distancias y crear mapas 2D o en el caso de 3D, nubes de puntos tridimensionales del entorno del robot. Estas nubes de puntos se pueden utilizar para generar mapas detallados del entorno, identificar obstáculos y calcular la posición del robot.

- Cámaras: son sensores visuales que capturan imágenes del entorno del robot. Estas imágenes se pueden utilizar para detectar objetos, reconocer patrones y características del entorno, además de realizar tareas de navegación visual. Las técnicas de visión por computadora, como el reconocimiento de objetos y la odometría visual, se utilizan comúnmente para procesar las imágenes de las cámaras y extraer información útil para la navegación y el mapeado [48], [49], lo cual, no solo mejora la seguridad y eficiencia de los robots móviles, sino que también contribuye significativamente a su autonomía y adaptabilidad. Diferentes técnicas de visión por computador han permitido a los robots móviles realizar tareas de mapeo, localización y navegación en entornos desconocidos con una mayor precisión. Investigaciones como la de Takafumi [18] demuestran cómo algoritmos avanzados de procesamiento de imágenes y reconocimiento de patrones permiten a los robots interpretar su entorno y tomar decisiones en tiempo real. Paralelamente, el uso de técnicas visuales de reconocimiento y seguimiento de objetos ha mejorado la capacidad de los robots móviles para interactuar y colaborar con los humanos en entornos de trabajo compartidos. Trabajos como el de Cartucho[50] resaltan cómo la integración de técnicas de aprendizaje profundo en sistemas basado en visión artificial permiten a los robots reconocer objetos, personas y situaciones complejas.

- Ultrasonido: los sensores ultrasónicos emiten ondas sonoras de alta frecuencia y miden el tiempo que tarda en recibir el eco de vuelta para calcular la distancia a los objetos en el entorno del robot. Estos sensores son útiles para la detección de obstáculos cercanos y la navegación en espacios interiores donde la señal de GPS puede ser débil o inexistente.

- Radar: utiliza ondas de radio en lugar de luz láser para detectar objetos y medir distancias. Los sistemas de radar son útiles para la detección de objetos en condiciones de poca visibilidad, como la lluvia, la niebla o la oscuridad, y se utilizan a menudo en aplicaciones de vehículos autónomos para complementar otros sensores.

- IMU (Unidad de Medición Inercial): miden la aceleración lineal y la velocidad angular del robot. Estos datos se utilizan para estimar cambios en la orientación y la posición del robot, lo que es útil para la navegación inercial y la corrección de errores de movimiento en combinación con otros sensores.

Al combinar varios tipos de sensores y técnicas de procesamiento de datos, los robots móviles pueden construir representaciones detalladas y precisas de su entorno, lo que les permite navegar de manera segura y eficiente en una variedad de entornos y condiciones. La fusión de sensores se emplea en robótica con el objetivo de mejorar la percepción artificial de los robots, permitiendo obtener una representación más completa y precisa del entorno que los rodea. Cada tipo de sensor obtiene una determinada información del entorno, con ciertas limitaciones. La fusión de sensores consiste en tomar información de sensores diferentes (p. ej. LiDAR y cámaras) y unirlas de manera que la información proporcionada por cada sensor complemente al otro, superando así sus limitaciones y obteniendo una percepción más rica en información [51]. Esta representación más fidedigna de su entorno les permite interactuar de modo más efectivo con su entorno y realizar tareas de manera autónoma con mayor eficiencia y seguridad.

Además de ampliar el rango de percepción, la fusión también proporciona redundancia y robustez al sistema, ya que si un sensor falla o produce datos inexactos debido a condiciones adversas, otros sensores pueden compensar esa pérdida logrando una información resultante más confiable. Aportan también mayor adaptabilidad a diferentes entornos ya que estos pueden variar en términos de iluminación, condiciones climáticas y tipos de obstáculos, que afectan en diferente medida a diferentes tipos de sensores. La fusión de sensores permite a los robots adaptarse a diferentes condiciones ambientales al utilizar la información de sensores específicos para cada situación, aumentando su versatilidad.

Una configuración muy común en robótica móvil se basa en la combinación de los datos de cámaras de visión artificial, LIDAR y sensores inerciales, proporcionando una representación completa y precisa del entorno. En la revisión dirigida por Alatise [52], realizan un estudio sobre los sensores más novedosos y utilizados en la actualidad junto con técnicas de fusión de sensores.

Mapeado

Se denomina mapeado al proceso que implica la creación y actualización de los mapas por donde navega el robot. Estos mapas son esenciales para que el robot pueda comprender su entorno, planificar rutas y evitar obstáculos de manera eficiente. El mapeado se puede realizar utilizando diferentes enfoques y sensores, pero su objetivo principal es capturar la estructura y las características del entorno con la mayor precisión posible. Los mapas de ocupación son representaciones gráficas y digitales de la realidad, los cuales indican qué áreas de un entorno están ocupadas y cuáles están libres. El mapa se actualiza continuamente a medida que el robot se desplaza y utiliza información de sensores para detectar obstáculos. El proceso de creación de mapas se puede generalizar en tres pasos iterativos:

1. Estimación del desplazamiento: en cada paso se estima cómo se ha desplazado el robot desde el paso anterior, creando un grafo con las posiciones que ha recorrido el robot y su lectura de sensor asociada.

2. Registro (*matching*) de nuevas lecturas y acumulación de las mismas en el mapa: en cada paso la lectura del sensor se registra contra el mapa y se acumula, haciendo correcciones si es necesario a la estimación previa del desplazamiento.

3. Cierre de lazo (*loop closure*): cuando se detecta que el robot ha regresado a una posición conocida, se utiliza el ajuste realizado en ese paso para corregir el grafo seguido hasta alcanzar la posición en curso, haciendo que las dos posiciones

coincidan en el mapa. En la Figura 4.3 obtenida del trabajo de Sherine Rady [53], se observa una captura del proceso de SLAM justo antes del cierre de lazo. La incertidumbre global (elipses grises) aumenta con la distancia. Un emparejamiento deficiente del escaneo en la parte inferior derecha introduce un pequeño error angular que conduce a un gran error en la estimación de la posición cuando el robot regresa al punto de partida (parte superior derecha). Las imágenes insertadas son las dos vistas de la cámara (actual y emparejada) que se utilizan para cerrar el lazo y corregir la posición. La imagen de la derecha muestra el mapa corregido después de detectar el cierre de lazo.

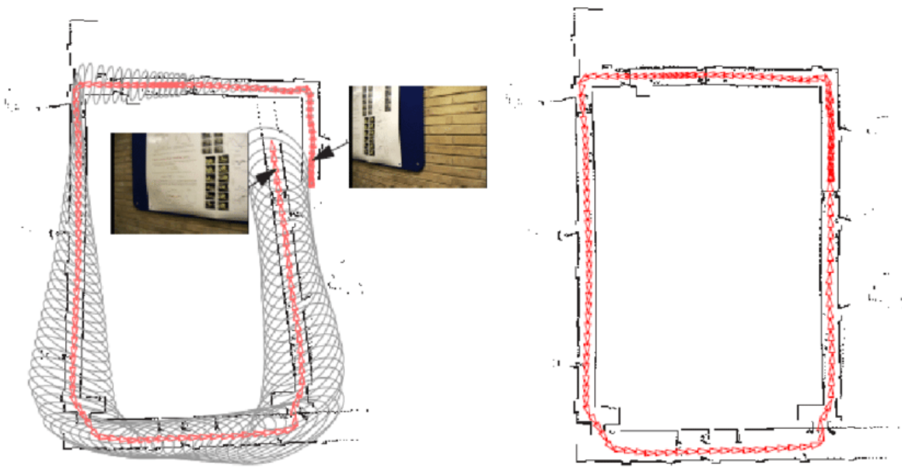

Figura 4.3: Cierre de lazo en la creación de mapas

Existen diferentes tipos de mapas de ocupación según su naturaleza:

- Mapas de ocupación binarios: cada celda se clasifica como ocupada (1) o libre (0). Es la forma más básica de ocupación de rejilla y se utiliza en entornos donde solo se necesita una representación simple de la ocupación del espacio.

- Mapas de ocupación probabilísticos: en lugar de asignar valores binarios, se asignan probabilidades a cada celda para representar la incertidumbre en la ocupación [54]. Esto permite una representación más flexible y precisa del conocimiento del robot sobre el entorno.

- Mapas de ocupación de logaritmo de probabilidades: este enfoque utiliza logaritmos de probabilidades para manejar de manera eficiente las operaciones de actualización de probabilidad. Es común en algoritmos de filtro bayesiano, como el filtro de Kalman extendido (EKF) [55] y el filtro de partículas.

- Mapas de ocupación aumentados: pueden incluir información adicional, como la altura de los objetos, para representar entornos 3D de manera más completa. Se utilizan en aplicaciones donde se requiere una representación tridimensional del entorno.

- Mapas de ocupación adaptativas: ajustan dinámicamente el tamaño de las celdas en función de la importancia percibida de diferentes regiones del entorno, esto puede ayudar a mejorar la eficiencia del mapeo en áreas críticas.

Localización

Dentro del campo de la navegación autónoma en robots móviles, los algoritmos de localización juegan un papel crítico en determinar la posición y orientación del robot en relación con su entorno. Estos algoritmos permiten que el robot sepa dónde se encuentra y cómo se está moviendo, lo que es esencial para la toma de decisiones autónoma y la navegación eficiente. A continuación se describen algunos de los algoritmos de localización más utilizados:

- Filtro de Kalman: es un método de estimación que utiliza una serie de mediciones imprecisas y ruidosas para calcular una estimación más precisa de la posición y la velocidad del robot. Este algoritmo se basa en modelos probabilísticos y es particularmente útil cuando se combinan múltiples fuentes de información, como la odometría y los datos de los sensores.

- Filtro de Partículas (Particle Filter): se trata de métodos de estimación que utilizan una colección de muestras, también denominadas partículas, para representar la distribución de probabilidad sobre la posición del robot. Estas partículas se propagan y actualizan utilizando mediciones de sensores y modelos de movimiento del robot. Los filtros de partículas son robustos y pueden manejar de manera efectiva la incertidumbre y la no linealidad en el problema de la localización.

- Localización basada en Histograma: este enfoque divide el espacio del mapa en celdas y mantiene un histograma que representa la probabilidad de que el robot se encuentre en cada celda. El algoritmo actualiza el histograma utilizando mediciones de sensores y modelos de movimiento, lo que permite al robot estimar su posición en función de la evidencia acumulada.

- Localización basada en EKF (filtro de Kalman extendido): es una extensión del filtro de Kalman clásico que puede manejar sistemas no lineales. Este enfoque se utiliza comúnmente en la fusión de datos de sensores para la localización, especialmente cuando se utilizan sensores como IMUs y cámaras que generan mediciones no lineales.

La elección del algoritmo adecuado depende de varios factores, como la precisión requerida, el entorno de operación y los recursos computacionales disponibles. En muchos casos, la combinación de varios algoritmos o técnicas de fusión sensorial puede proporcionar la mejor precisión y robustez en la localización del robot.

La técnica SLAM (*Simultaneous Localization and Mapping*) permite a un robot construir un mapa del entorno desconocido mientras determina su propia posición dentro de ese mapa en tiempo real. La idea principal detrás de SLAM es resolver el problema de la localización del robot y el problema del mapeo del entorno simultáneamente. Para lograr esto, los robots utilizan una combinación de sensores, como cámaras, LIDAR, IMU (Unidad de Medición Inercial) y sensores de distancia, junto con algoritmos de procesamiento de datos. Existen varias aproximaciones para implementar SLAM, que van desde métodos basados en el filtro de Kalman extendido (EKF) hasta enfoques probabilísticos como el filtro de partículas y métodos basados en optimización como el SLAM basado en grafo. Cada método tiene sus propias ventajas y desventajas en términos de precisión, eficiencia computacional y robustez en diferentes tipos de entornos.

Planificación de rutas

La planificación de rutas se refiere al proceso de determinar un camino óptimo y seguro para que un robot se mueva desde su posición actual a un destino deseado en un entorno conocido. Los algoritmos de planificación de rutas tienen en cuenta una serie de factores como los posibles obstáculos, las restricciones de movimiento del robot, la eficiencia energética y el tiempo de llegada, entre otros.

Existen varias técnicas y algoritmos de planificación de rutas entre los que se destacan los algoritmos de búsqueda de grafos como A* [56], Dijkstra [57] y D*, utilizados para encontrar el camino más corto entre dos puntos en un mapa. Estos utilizan estructuras de datos como grafos para representar el entorno y exploran diferentes rutas para encontrar la óptima.

Como alternativa a métodos puramente geométricos, en lugar de simplemente encontrar un camino entre dos puntos, la planificación de trayectorias considera la dinámica del robot y genera una secuencia de puntos a través de los cuales el robot puede seguir su camino de manera suave y continua. Algoritmos como RRT (*Rapidly-exploring Random Tree*) y PRM (*Probabilistic Roadmap*) son comunes en este enfoque.

Algunos de los métodos de planificación de trayectorias más extendidos en la actualidad son los basados en muestreo y en curvas:

- Muestreo:
  - DWA (*Dynamic Window Approach*) [58]: se trata de un algoritmo de planificación local basado en la idea de "ventanas dinámicas", las cuales representan conjuntos de posibles velocidades lineales y angulares del robot. El objetivo es seleccionar la mejor ventana dinámica que maximice ciertos criterios de rendimiento, como la proximidad al objetivo y la evitación de obstáculos. DWA es rápido y eficiente para entornos dinámicos, ya que adapta continuamente la planificación a medida que cambia el entorno.
  - SBPL (*Search-Based Planning Library*) [59]: se trata de un algoritmo de planificación global que representa el espacio de estados del robot y utiliza técnicas de búsqueda, como A*, para encontrar la mejor ruta posible desde el estado inicial al estado objetivo. Puede manejar restricciones y considerar la dinámica del robot y del entorno. SBPL es adecuado para entornos estáticos o semiestáticos donde es capaz de proporcionar mejores soluciones en términos de coste.
- Curvas:
  - EB (*Elastic Band*) [60]: es un algoritmo utilizado para la planificación de trayectorias en entornos dinámicos. Se basa en un modelo que evita colisiones al deformar una "banda elástica" alrededor del robot y los obstáculos, minimizando la interferencia entre ellos adaptando la forma de la banda elástica al entorno. EB es adecuado en situaciones donde el entorno es dinámico y cambia con el tiempo.
  - TEB (*Timed Elastic Band*) [61]: es una extensión del algoritmo Elastic Band que incorpora el tiempo en la planificación de trayectorias. Optimiza la duración de la trayectoria teniendo en cuenta restricciones temporales como la velocidad máxima y mínima del robot. TEB es útil en situaciones donde la sincronización temporal es crítica, como en robots que deben cumplir con ciertos plazos o velocidades específicas.

Otras técnicas empleadas comúnmente son las basas en campos potenciales. Estas utilizan un modelo de campo potencial en el que el robot es atraído hacia el objetivo y se aleja de los obstáculos. El campo se calcula continuamente a medida que el robot se mueve y se utiliza para guiar el movimiento del robot hacia su objetivo. Uno de los trabajos más relevantes en la utilización de campos potenciales artificiales es el propuesto por L. Tang [62] donde aportan una solución al problema de convergencia en mínimos locales. Para ello, se basan en cadenas de gravedad donde aplican el concepto de bandas elásticas que conectan con el principio y el final en el espacio del campo potencial de obstáculos.

En los trabajos más recientes se presentan novedosas soluciones basadas en técnicas clásicas de planificación de rutas mediante algoritmos de búsqueda, adaptados a los sistemas modernos. En el trabajo presentado por Miao et al. [63], los autores proponen un algoritmo basado en el comportamiento de colonias de hormigas (IAACO) que obtiene rutas globales optimizadas y un alto rendimiento en tiempo real y estabilidad. La aplicación de algoritmos metaheurísticos en la planificación de rutas ha llamado la atención de investigadores de la comunidad robótica debido a la simplicidad de los enfoques y su eficacia en la coordinación de los agentes. En el estudio realizado por MN Ab Wahab [64] se explora la implementación de muchos algoritmos metaheurísticos, como por ejemplo: algoritmos genéticos (GA), evolución diferencial (DE) u optimización de enjambre de partículas (PSO) en múltiples escenarios. El estudio proporciona también una comparación entre múltiples enfoques metaheurísticos con un conjunto de técnicas de navegación y planificación de movimiento convencionales bien conocidas, como el algoritmo de Dijkstra (DA), la hoja de ruta probabilística (PRM), el árbol rápidamente aleatorio (RRT) y el campo potencial (PF). Los resultados muestran la competitividad de los enfoques metaheurísticos frente a los métodos convencionales.

Control de trayectorias

Una vez que se ha planificado una ruta, el siguiente paso es implementar algoritmos de control para que el robot siga fielmente esa ruta. Dentro de los modelos clásicos, el control proporcional derivativo integral (PID), es uno de los métodos de control más utilizados en robótica. Se basa en ajustar continuamente la salida de control del robot en función del error entre su posición actual y la posición deseada en la ruta planificada.

El control de trayectoria se centra en seguir una trayectoria predeterminada generada por el algoritmo de planificación de trayectorias ajustando continuamente los comandos de control del robot para mantenerlo dentro de la trayectoria planificada. Existen soluciones de control denominadas de lazo abierto donde el sistema de control no tiene en cuenta el estado del sistema y su resultado y, de lazo cerrado, donde el sistema de control es realimentado con información del estado del robot, como su posición y velocidad, para calcular y ajustar los comandos de control necesarios para seguir la ruta planificada. En la Figura 4.4 se pueden observar dos estrategias de seguimiento de una trayectoria: en el primer caso, el controlador intenta aproximarse a la trayectoria usando el punto más cercano como referencia, esto origina una trayectoria más precisa; en cambio, en el segundo caso el robot intenta aproximarse a un punto de la trayectoria que se sitúa en T+X de la posición actual, generando una trayectoria más suave.

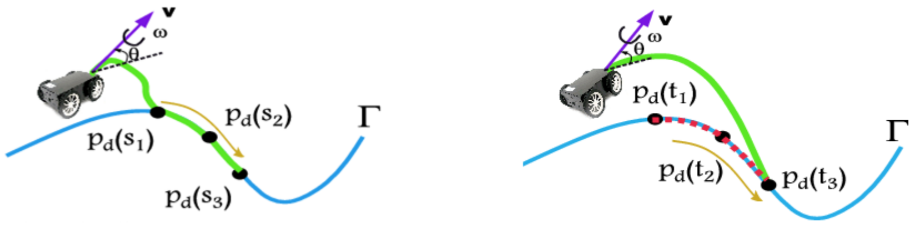

Figura 4.4: Ejemplo de dos estrategias de seguimiento de una trayectoria

La combinación de una planificación de rutas efectiva y algoritmos de control precisos es esencial para lograr una navegación autónoma exitosa en robótica móvil, permitiendo que los robots se muevan de manera segura y eficiente en entornos complejos y dinámicos.

4.3.3. Manipulación inteligente

La manipulación de objetos con robots en aplicaciones industriales es un área en constante desarrollo que busca mejorar la eficiencia y seguridad en los entornos de trabajo. Los últimos avances en algoritmos de manipulación autónoma han permitido manipular objetos y herramientas adaptándose a diferentes formas, tamaños y pesos. Esta mejora en las capacidades ha venido de la mano de una mayor sensorización de los robots que, equipados con sensores avanzados como cámaras y sensores táctiles, les permiten percibir su entorno, detectar la presencia de humanos y reaccionar de manera segura en tiempo real. Uno de los sensores más relevantes y avanzados son los sensores de fuerza y par, que les permiten ajustar la fuerza aplicada según las necesidades de la tarea, lo que es esencial para la manipulación precisa de objetos. Todo esto facilita la colaboración directa entre humanos y robots en un entorno compartido, minimizando el riesgo de lesiones.

Para facilitar su despliegue en entornos industriales, los robots deben incorporar interfaces de programación intuitivas, permitiendo a los usuarios sin experiencia en programación crear tareas específicas y complejas, como la manipulación de objetos, a través de interfaces gráficas o comandos simples. En el trabajo publicado por De Martini [65], se presenta las carencias y necesidades de las interfaces de usuario actuales y propone una interfaz intuitiva y modular que ayuda a los operarios a realizar sus operaciones con los robots.

El control de los robots es esencial para garantizar la correcta y segura manipulación de los objetos, basándose en técnicas y algoritmos utilizados para dirigir, coordinar y supervisar el movimiento de los ejes y articulaciones del manipulador. Los tipos de controles más utilizados son el control en posición y velocidad, y el control por fuerza e impedancia, como el utilizado en [66] para manipular largas piezas aeronáuticas. El control basado en visión artificial, en el que se utiliza información visual para ajustar y mejorar la precisión de las operaciones, implicando el uso de cámaras y algoritmos de procesamiento de imágenes para guiar el brazo hacia su objetivo. En el libro [67] se establecen las bases de este tipo de control, conocido como *Visual Servoing*.

Finalmente, se encuentran los algoritmos de planificación de trayectorias que determinan la ruta más eficiente y segura para que el robot alcance su destino, evitando obstáculos y cumpliendo con restricciones cinemáticas.

Los algoritmos de planificación de trayectorias más utilizados son los basados en métodos probabilísticos como RRT (*Rapidly-exploring Random Trees*) o PRM (*Probabilistic Roadmaps*), ya que son útiles para la planificación de trayectorias en entornos complejos o desconocidos, donde se necesitan considerar múltiples obstáculos y restricciones. En trabajos como [68], se propone un método autónomo de planificación dinámica de rutas para evitar obstáculos para un manipulador robótico basado en un algoritmo RRT mejorado, llamado Smoothly RRT (S-RRT), el cual obtiene grandes resultados de planificación en diferentes robots reales.

Gracias a estos avanzados sistemas complementarios de control y percepción artificial, las trayectorias calculadas son capaces de evitar obstáculos conocidos y no conocidos, por lo que permiten a los AIMM operar en entornos dinámicos y cambiantes. Una de las soluciones más extendidas para la generación de trayectorias libres de colisión mediante percepción artificial es la suite *Moveit!* [69], gracias a su integración en el *middleware* ROS [70].

Contribuciones 5

Al analizar la situación actual y la tendencia futura de la industria y los procesos productivos, se observa una gran demanda de tecnologías versátiles y adaptables que permitan dar respuesta a situaciones de alta variabilidad y producción en pequeños lotes. Existe un cambio de paradigma en las necesidades actuales de la fabricación que está provocando una transición del enfoque actual basado en la producción en masa a un enfoque de personalización en lotes, donde los volúmenes de producción son más pequeños y variables. Esto es conocido como "*High-mix, low-volume*". Los procesos actuales están muy adaptados al paradigma anterior y carecen de la flexibilidad necesaria para adaptarse a las nuevas necesidades de producción. Esto es sumado a una disminución en la disponibilidad de operadores capacitados debido al envejecimiento de la población, por lo que adaptarse a este nuevo escenario representa un desafío para las empresas, especialmente las pequeñas y medianas empresas (Pymes), que están experimentando cómo su especialización se vuelve en su contra de manera evidente.

Este proyecto de tesis pretende dar respuesta y mitigar los efectos de esta transición industrial, denominada Industria 4.0, mediante la integración de la robotización y la automatización, así como la incorporación de novedosas técnicas basadas en inteligencia artificial y sensórica moderna para lograr una mayor percepción artificial y, por tanto, una mayor capacidad, autonomía y versatilidad en los procesos productivos. Las principales contribuciones de este trabajo se pueden clasificar en tres grandes pilares:

- Diseño de Robots: diseño de nuevas soluciones robotizadas basadas en AIMMs para dar respuesta a las necesidades actuales de la industria.
- Sensórica avanzada: selección de sensores para mejorar la percepción artificial del sistema. Los sensores utilizados son:

- Cámaras 2D, 3D y RGBD con técnicas de visión por computador para detección de modelos y patrones.
- LIDAR 2D y 3D para tareas de mapeado, localización y seguridad del sistema.
- Encoders para obtener la odometría del robot.
- IMU para obtener aceleraciones, rotaciones e inercias que favorecen la estimación de la odometría del robot.

Fusión de la información de sensores mediante filtros extendidos de Kalman para refinar y ajustar los resultados.

- Navegación autónoma 2D y 3D: mapeado del entorno, localización, planificación de trayectorias y control de las mismas. Navegación precisa para ajuste del robot mediante técnicas de visión artificial. Seguimiento de sistemas en movimiento para realizar tareas de montaje (*Do while moving*)

- Capacidad para manipular e interactuar de forma versátil y eficaz con elementos del entorno.

Dichas contribuciones, que han sido apoyadas en diferentes proyectos europeos y nacionales, descritos en la sección 3.3, pueden verse plasmadas en los siguientes artículos publicados en congresos y revistas indexadas con un impacto Q4 o superior. Los artículos resaltados avalan la investigación y pueden encontrarse adjuntos en la Parte II de este trabajo.

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- **PATENTE Nº: P232555EP**

6 Conclusiones

La presente investigación ha representado un paso adelante hacia la integración efectiva de soluciones robotizadas en entornos industriales modernos, caracterizados por la producción en lotes pequeños y altamente personalizados. A través del diseño y la implementación de nuevos robots denominados Autonomous Industrial Mobile Manipulators (AIMMs), se ha abordado la necesidad creciente de flexibilidad en los procesos productivos, contribuyendo así a la evolución de la Industria 4.0.

Una de las principales contribuciones de este trabajo ha sido el diseño innovador de robots adaptados específicamente para las demandas cambiantes de la industria actual. Estos robots han sido concebidos para optimizar la flexibilidad y la eficiencia en la ejecución de tareas variadas y personalizadas.

La integración de una amplia gama de sensores avanzados ha mejorado significativamente la percepción artificial de los AIMMs diseñados. La utilización de cámaras 2D, 3D y RGBD, junto con LIDAR 2D y 3D, encoders e IMU, ha permitido una detección precisa de modelos y patrones, así como un mapeado detallado del entorno y una estimación precisa de la odometría del robot. La fusión de la información de estos sensores ha sido fundamental para refinar y ajustar los resultados obtenidos, garantizando una mayor precisión en la ejecución de las tareas asignadas.

La implementación de algoritmos de navegación autónoma 2D y 3D ha dotado a los AIMMs de la capacidad de mapear el entorno, localizarse con precisión, planificar trayectorias y controlar su movimiento de manera autónoma. El desarrollo de algoritmos basados en técnicas de visión artificial han permitido realizar tareas de montaje y fabricación de modo preciso y eficiente, incluso en tareas en movimiento, donde la pieza avanza por la planta de producción sobre un vehículo o cinta transportadora y el robot la sigue y realiza tareas sobre ella.

Se ha demostrado la capacidad de los AIMMs para manipular e interactuar de manera versátil y efectiva con elementos del entorno, lo que amplía significativamente su utilidad en una amplia gama de aplicaciones industriales.

En resumen, este trabajo de tesis ha proporcionado una sólida base para el desarrollo y la implementación de soluciones robotizadas basadas en AIMMs en el contexto de la Industria 4.0. Las contribuciones realizadas en términos de diseño de robots, selección y fusión de sensores, navegación autónoma y capacidad de manipulación versátil representan avances significativos que tienen el potencial de transformar los procesos industriales modernos hacia una mayor eficiencia, flexibilidad y personalización.

6.1. Trabajo Futuro

El avance continuo en la implantación de la robótica en la industria moderna, dentro del contexto de la Industria 4.0, plantea una serie de desafíos y oportunidades para el futuro. Algunos trabajos pendientes que podrían contribuir al desarrollo y mejora de este área se pueden clasificar en nuevos ámbitos de aplicación, y en la integración de nuevas tecnologías.

6.1.1. Nuevos ámbitos de aplicación

A pesar de que la navegación autónoma para interiores o *indoor* ha avanzado significativamente en los últimos años, con robots capaces de moverse de manera precisa en entornos semi controlados como almacenes o fábricas, la navegación para exteriores, *outdoor*, presenta desafíos adicionales que requieren soluciones específicas.

Uno de los principales obstáculos en la navegación outdoor es la variabilidad del entorno. Los robots deben lidiar con terrenos irregulares, cambios en las condiciones climáticas, obstáculos impredecibles y una mayor diversidad de superficies. Esto requiere algoritmos de navegación más sofisticados que puedan adaptarse a entornos dinámicos y tomar decisiones en tiempo real para evitar obstáculos y planificar rutas eficientes.

La navegación outdoor también plantea desafíos en términos de conectividad y percepción del entorno. Los robots deben ser capaces de mantener la comunicación con sistemas de control remoto o redes de satélites para recibir actualizaciones de posición y datos ambientales. Además, necesitan sistemas de percepción avanzados, como cámaras, sistemas láser y sensores de proximidad, para detectar y evitar obstáculos de manera efectiva.

Trabajar en soluciones de navegación outdoor fiables y robustas requiere un enfoque multidisciplinario que combine la ingeniería robótica, la inteligencia artificial, la percepción artificial y la planificación de rutas. Es fundamental realizar pruebas exhaustivas en una variedad de entornos y condiciones para garantizar que los robots puedan funcionar de manera segura y eficiente en el mundo real.

De acuerdo a las demandas de la industria moderna, las nuevas soluciones basadas en robots móviles autónomos deben ser capaces de enfrentarse a situaciones mixtas. Esto es, navegar de modo autónomo y eficiente tanto en entornos indoor como outdoor y ser capaces de adaptarse a estos cambios de entorno del modo más rápido posible reconfigurando sus parámetros y sensores requeridos.

Otro aspecto interesante a tener en cuenta en trabajos futuros es la ética y responsabilidad social. A medida que la robótica se integra más profundamente en la industria, es importante abordar las implicaciones éticas y sociales de su uso. Esto incluye consideraciones sobre el impacto en el empleo, la equidad y la distribución de la riqueza, así como el desarrollo de marcos regulatorios y éticos adecuados.

6.1.2. Nuevas tecnologías

La integración de nuevas tecnologías en los procesos productivos actuales y, concretamente en la robótica, es esencial para el correcto desarrollo de soluciones innovadoras y prometedores en la industria. Tecnologías como la inteligencia artificial (IA) y el aprendizaje automático (ML) permitirá a los robots tomar decisiones más autónomas y adaptativas en entornos industriales complejos y dinámicos. Además de reducir considerablemente el tiempo dedicado a la programación y puesta en marcha de los robots, ya que pueden aprender nuevas capacidades y mejorar las ya conocidas de modo no supervisado.

La integración de Modelos de Lenguaje de Gran Escala (LLMs) en la robótica proporciona una serie de beneficios que pueden mejorar la capacidad de los robots para comprender, comunicarse y colaborar con los humanos, consiguiendo sistemas robóticos más inteligentes, adaptables y útiles en una variedad de contextos y aplicaciones.

La interacción natural permite que los robots comprendan y generen lenguaje natural de manera más efectiva, lo que facilita la comunicación y la interacción con los humanos. Esto es especialmente útil en entornos donde se requiere colaboración estrecha entre humanos y robots. Además, los LLMs pueden entender el contexto de una conversación o situación, lo que les permite interpretar mejor las solicitudes y responder de modo relevante y preciso. Esto es crucial para tareas como la navegación en entornos complejos o la ejecución de instrucciones específicas en entornos cambiantes. A su vez, los LLMs pueden adaptarse y mejorar continuamente a medida que interactúan con los humanos y reciben retroalimentación. Esto significa que los robots pueden aprender de experiencias pasadas y mejorar su rendimiento con el tiempo, lo que los hace más efectivos en una variedad de situaciones.

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Parte II

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Innovative Mobile Manipulator Solution for Modern Flexible Manufacturing Processes

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Abstract: There is a paradigm shift in current manufacturing needs that is causing a change from the current mass-production-based approach to a mass customization approach where production volumes are smaller and more variable. Current processes are very adapted to the previous paradigm and lack the required flexibility to adapt to the new production needs. To solve this problem, an innovative industrial mobile manipulator is presented. The robot is equipped with a variety of sensors that allow it to perceive its surroundings and perform complex tasks in dynamic environments. Following the current needs of the industry, the robot is capable of autonomous navigation, safely avoiding obstacles. It is flexible enough to be able to perform a wide variety of tasks, being the change between tasks done easily thanks to skills-based programming and the ability to change tools autonomously. In addition, its security systems allow it to share the workspace with human operators. This prototype has been developed as part of THOMAS European project, and it has been tested and demonstrated in real-world manufacturing use cases.

Keywords: industrial mobile manipulator; robotics; perception; sensor fusion; autonomous navigation; skill-based programming; Industry 4.0

1. Introduction

The manufacturing industry is changing. Many traditional industrial sectors have been based on the serial production line paradigm for decades. By constantly evolving their industrial processes to optimize results and be increasingly efficient, they have achieved a highly efficient manufacturing of products, but always based in the manufacturing of large batches of identical products.

In recent years, however, there is a significant shift in market needs [1]. Product personalization and differentiation have become a key factor when purchasing a wide variety of nonbasic products. The paradigm shift is evident in multiple markets, such as cars or electronics, resulting in switching manufacturing processes from *Low Mix/High Volume* to *High Mix/Low Volume* productions. The adaptation to this new production paradigm, recently known as "*mass customization*" [2], is key to keeping the manufacturing companies' competitiveness in these sectors. Further, other industries with low throughput but high product variability, such as aeronautics, can greatly benefit from this paradigm shift.

Traditional robotics with its programmable automatons of great repeatability does not respond to the current market demand for changing products with small production batches [3]. The robustness and efficiency of the serial production model is highly compromised by the need to perform changes in production equipment, which lacks the cognitive capabilities to support multiple operations in a dynamic environment [4]. This is due to the non-adapatability of traditional robots and the high cost of changing a task to a different one. Very invasive changes in the area and a lot of reprogramming time by qualified specialists are required. This remains expensive due to limited access to skilled operators caused by an aging workforce and faster technology development, even with recent advances in education [5]. This requires new solutions to assist operators and provide collaborative work environments [6].

In any case, the latest reports reveal that at least 85% of the production tasks in major industries (computers and electronics; electrical equipment, appliances and components; transportation equipment; machinery) are automatable involving assembly/tending of machines which are highly repetitive [7]. Thus, even in the case of mass customization, automation and smart scheduling of production lines [8] are the keys to efficient manufacturing.

In order to adapt to new market demands and the needs of modern industrial processes, a new industrial robot has been designed and manufactured. The robot can be classified as an autonomous industrial mobile manipulator (AIMM), since it meets all the criteria established in [9] where different types of mobile manipulators are presented. This kind of robots are currently an important trend in research, with several recent commercial and research examples available [10–13]. Different AIMMs have been designed and manufactured for a variety of purposes, including tasks such as polishing, sanding, painting, assembly, packaging, logistics, and other challenges of modern industrial processes.

It is equipped with a large number of built-in sensors which give the robot the ability to perceive its surroundings as well as greater autonomy and adaptability. In addition to traditional safety sensors (i.e., safety lasers scanners), a range of complementary ones have been carefully chosen in order to provide the robot with the ability to work together with people safely and without barriers [14].

As it is a mobile manipulator, this new robot has the ability to navigate autonomously through the work cell thanks to its powerful motorwheels and navigation software solutions. Current navigation techniques are very mature approaches but do not respond to all the needs of modern industry. Infrastructure based navigation systems successfully used in industrial environments—e.g., automatic guided vehicles (AGVs)—lack the necessary flexibility and require a high initial investment. For this reason, more and more approaches are being used in the industry based on 2D navigation techniques for static environments, together with the already well-known intelligent path planning techniques [15], dynamic obstacle avoidance [16], and location in the environment [17]. However, these solutions, on many occasions, are not accurate enough for low tolerance operations common in manufacturing, such as part assembly or picking. Approaches using 3D mapping have been introduced to improve robustness in infrastructure-less navigation, using truncated signed distance functions in voxel maps [18] or multiresolution surfel maps [19]. A final accurate approach or docking is thus necessary to complement standard navigation techniques and achieve adequate positioning accuracy.

As a novelty in current mobile manipulators [20], the presented robot incorporates a torso and two arms that allow it to execute more complex tasks and support a greater payload. The control is a software layer based on the robot operating system (ROS) framework [21,22] that eases programming. ROS is a widespread and mature robotic middleware with a large base community of developers, and it is the de facto standard robotics software in the research community.

This AIMM has been carefully designed to be able to address as many of the potential tasks that currently take place in manufacturing processes as possible. The capabilities of this AIMM are being explored as part of the ongoing EU project THOMAS [23], where it is known as the Mobile Robotic Platform (MRP) (Figure 1). This project, with a planned duration of four years, is a framework of collaboration for a consortium of both industrial and R&D partners. The aim of the project is to assess a variety of technological aspects of a new generation of manufacturing systems adapted to the flexibility of the mass customization paradigm (e.g., perception, safety, human–robot interaction, and resource management). The technologies developed by the different partners will be integrated into an industrial robotics solution and tested in two use cases from industrial partners in the automotive (PSA) and aeronautics (Aernnova) sectors. These use cases have enough variety in tasks and operations to demonstrate the versatility of the approach [24].

Figure 1. The Mobile Robotic Platform (MRP) navigating autonomously to the charging station.

This paper is devoted to providing a detailed description of the components and systems of the proposed MRP's prototype. In the following subsections, the project objectives (Section 1.1) and the automotive and aeronautic use cases (Section 1.2) are described. In Section 2, the technical description of the robot is presented. It includes the drive system selected for mobility, a description about the manipulators equipped, and details about sensors and safety components to improve the perception and the autonomy of the robot. Section 3 reviews current navigation techniques and how we use and enhance these techniques to add new capabilities to the robot. These capabilities allow it to reach positions accurately and to improve the cycle times of processes through the ability to work during robot movement. Section 4 describes the skills-based programming that has been applied to our development. Finally, in the last sections, several tests of the system and their results are presented and discussed (Section 5). The paper ends with some conclusions and the following steps in the system development (Section 6).

1.1. Objectives

The fourth industrial revolution, called Industry 4.0, demands certain requirements that cutting-edge companies must achieve to attain a satisfactory degree of efficiency [25]. The industry demands have been analyzed, resulting in a proposal of a range of solutions that the presented 4.0 sensorized robotic solution approach is able to offer.

Table 1 shows the needs of the industry for the selected use cases and the objectives that our solution tries to achieve.

Table 1. Proposed solutions to the industrial needs of the selected use cases.

Industrial Requirements	Objectives
Layout reconfiguration of the production system	Enabling mobility on products and resources by means of mobile resources able to navigate in the shop floor and use dexterous tooling with embedded cognition functions that allow it to perform more than one assembly/logistics operations.
Awareness of real world uncertainty	Enabling perception of the task and the environment using: • the individual resource's sensors to adjust their operation to the real process requirements. • collaborative perception by combining sensors of multiple resources and shop floor sensors to collectively plan and execute production tasks.
Adaptation to non-expected situations	Fast programming and automatic execution of multiple tasks. By applying skills over the perceived environment to determine required task adaptation actions and also by automatically generating the robot program for new product variants.
Flexibility to combine different resource types	Safe collaboration between humans and robots eliminating physical barriers(fences, enclosures etc.) by introducing cognitive capabilities that will allow the robots combine different sources to detect the human and its intentions and ensure that no harmful action is taken.

1.2. Use Cases

1.2.1. Automotive Use Case

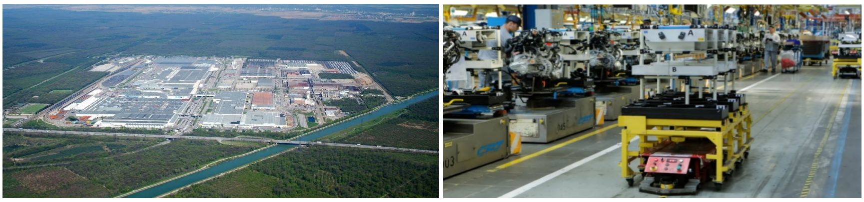
PSA is the car manufacturer of two world-famous brands, Peugeot and Citroën. In 2014, it was the second largest European automotive manufacturer and the 9th largest in the world measured by unit production. PSA is an active partner of THOMAS, providing to the consortium open access to the production line of the Mulhouse plant that is being considered under this project.

After a thorough study of the possible applications where the robot could offer a better response and be more autonomous and efficient [26], a complex task was identified that supposes a new technological challenge and of great applicability in the industry.

The process is based on the assembly of vehicle damper through a manual process in which several operators interact within an assembly chain. As it is an assembly line, the process is continuous. A filoguided AGV transports the disassembled parts of the damper onto a cart, and at each work station, an operator assembles the parts and leaves the result on the AGV's cart again, which navigates to the next work station, as can be seen in Figure 2b. This process is cyclic and ends when the damper is fully assembled. Cycle times are critical since the AGV has a predefined trajectory and already established downtime and movement. The maximum efficiency of the process is sought.

In order to save cycle times and take advantage of all the capabilities of the innovative AIMM, it has been proposed to carry out an AGV tracking and following task to perform a threading process of a damper clamping screw. Performing the task in motion greatly reduces the cycle time, since it is not necessary to stop the process, and it is an interesting challenge of manipulation, perception, and control that can help future industrial developments.

The AIMM must navigate autonomously, taking into account obstacles, people, and other unforeseen events from an area of the workshop, where it is performing other tasks, up to the proximity of the AGV. It must also make a previous tool exchange before reaching the AGV. As the autonomous laser-based navigation does not offer very precise results, a precise approximation to the AGV is necessary. Once the AGV starts and begins to move, following the magnetic tape that marks its trajectory, the AIMM must imitate its trajectory in a very precise way so that the robot manipulators can carry out the screw thread threading process. The manner in which the threading is performed and the techniques used are outside the purpose of this article.



(**a**) (**b**)

Figure 2. PSA facilities. (**a**) An aerial view of the plant. (**b**) One of the automatic guided vehicles (AGVs) of the plant transporting assembly pieces. ©PSA.

1.2.2. Aeronautic Use Case

Aernnova Aeroestructuras Alava (SA) is a company dedicated to the assembly of various aircraft structures and is part of the group Aernnova, as can be seen in Figure 3.

(**a**) (**b**)

Figure 3. Aernnova facilities. (**a**) Front view of the plant. (**b**) One of the assembly lines. ©Aernnova.

Aernnova plant covers an area of 19,900 m^2 and has around 600 employees. Currently, the assembly process is mainly manual, having only one automatic machine, CIMPA, for automatic drilling, countersinking, sealing, and riveting metallic skins.

Aernova's operations have a large number of processes performed manually, many of them with ergonomic problems. Several of them were selected, based on a search for those in which introductions of automation will have more impact in both efficiency and ergonomics.

The main focus was on the drilling process for the joining holes of both skins of a carbon fiber wing to the inner structure (ribs and spar). This drilling is done by means of drilling templates using an automatic drilling unit (ADU). Each template may include 40–70 holes that the robot should drill accurately.

The process presents several challenges which are currently the subject of study by many robotic researchers:

- The robot must acquire the ability to navigate between different workstations autonomously;
- Once inside the workstation, the robot must navigate more accurately to cope with the tight spaces inside the cell and position itself in front of the drilling structure within strict thresholds;
- The robot must be able to change the previously installed tools for the specific ones;
- It should detect all the holes on the template and calculate an obstacle-free trajectory to approach the drill to the structure;
- The perception system must be able to fix a possible incorrect self-referencing of the robot with the structure.

2. An Innovative Robot Design

The first and one of the most important phases of building the MRP robotic solution is the correct design of the prototype. Many things have to be taken into account since it is intended to automate as many tasks as possible. The simpler, classical approach of just attaching a robotic arm to a mobile platform, while providing greater versatility than traditional fixed robots, is not enough to cope with the tasks involved in modern industry, especially in the use cases of automotive and aeronautics where the results of this solution is to be validated. As stated previously, recently, many examples have appeared following the AIMM concept of more advanced, industry-ready manipulators [9–13,27]. From a preliminary study of the capabilities of such examples, the benefits and limitations of different systems have been identified, and the MRP has been designed trying to overcome their current limitations and to be able to successfully carrying out the tasks that modern industry is demanding. To do that, the following topics have been taken into account: mobility, manipulation, perception, safety, and autonomy. Table 2 shows a comparison of the main hardware characteristics of the solution proposed in this article (MRP) with other recent mobile manipulators.

Table 2. Comparison of our solution (MRP) with other different recent mobile manipulators.

Robot	Mobility	Manipulation	Perception	Reachability	Autonomy	Robot Payload
MRP	Omnidirectional Swerve drive 3 m/s	(2×) UR10 6 DOF 20 Kg	(2×) Lidar 2D (2×) Stereo camera (2×) HD camera RGB-D sensor IMU Wheel encoder Force Torque sensor	From floor to a 2.5 m Rotation covers 350° of amplitude	>8 h	400 kg
Kuka KMR iiwa	Omnidirectional Mecanum wheels 1 m/s	LBR iiwa 7/14 7 DOF 7/14 Kg	Lidar 2D Arm Force sensor	800–820 mm	-	170 kg
DLR Justin (research)	Omnidirectional Swerve drive 2 m/s	(2×) Kuka LWR 7 DOF 15 Kg	(2×) Stereo camera (4×) RGB-D camera Laser-stripe sensor Torque sensor (2×) IMU	From floor to a 2.7 m	>60 min	20 kg
Neobotics MM-700	Differential 1 m/s	UR10 6 DOF 10 Kg	Lidar 2D	1300 mm	<8 h	180 kg
ClearPath Ridgeback + Baxter	Omnidirectional Mecanum wheels 1.1 m/s	(2×) Custom arms 7 DOF 2/3 Kg	Lidar 2D IMU BumbleBee Stereo cam 360° Sonar sensor	1040 mm + optional pedestal	15 h Only base	100 kg
Robotnik JR2	Omnidirectional Mecanum wheels	AUBO-I5 6 DOF 5 Kg	(2×) Lidar 2D (2×) RGB-D sensor	9245 mm	8 h	100 Kg

2.1. Mobility

Mobility is one of the strengths of an AIMM, which is why it needs to be equipped with an adequate traction system.

An AIMM is expected to navigate through typical industrial workshops with flat, smooth grounds and very few ground-level obstacles. Thus, while small irregularities and obstacles should be surmountable, all-terrain capabilities are not required.

For the tasks that are going to be performed, the robot must have great mobility that allows it to reach all the objectives as easily as possible and without having to perform excessive maneuvers. For this reason, cinematic solutions with limited degrees of freedom such as Ackermman, Skid, and differential drives were discarded. Their limited mobility largely conditions the robot's behavior and ability to move in cluttered environments.

The choice of mecanum wheels [28] was considered initially due to their true holonomic movement capacity. It is a type of wheel widely used among modern mobile manipulators (Kuka KWR iiwa, Robotnik JR2, Clearpath Ridgeback). A robot equipped with them has three complete degrees of freedom, being able to seamlessly move in all directions of the plane, as well as rotate. It was considered a viable option as it provided the highest mobility capacities. However, concerns were raised regarding when combined move/manipulation tasks are performed. As the wheels are composed of small rollers, when they move, they generate vibrations that propagate throughout the robot, increasing its effect farther away from the origin of vibrations. In a robot of these dimensions, small vibrations on the wheels can cause a very significant oscillation in the tip of the arm's tool center point (TCP). For inspection tasks in motion, application of sealants or paints this system is not recommended.

The final drive configuration chosen for the MRP was a Swerve drive (full 2D drive train in which all wheels are steered) (see Section 3.1.2) composed of four motorwheels, as a good trade between mobility and stability. While not truly holonomic, the motorwheel swerve drive is fully omnidirectional, and the single, medium-sized wheels offer good stability and the capacity of overcome small obstacles and ground irregularities.

The wheels are made of a plastic material that reduces slippage and dampens small pavement damage. The wheels are driven by two large engines, one for translation and one for rotation, the drive system being composed of a total of 8 motors. It reaches a maximum speed of 3 m/s, although it is limited by software to 2 m/s for safety reasons.

The odometry of the robot is provided by the fusion of different sensors. The encoders installed on the wheels provide an approximation of the robot's odometry. As it is well known, these data are prone to errors (wheel slippage) and drift over time as the error accumulates. An inertial measurement unit (IMU) is also used as additional source of odometry by accumulating over time the provided accelerations data. Finally, a third source of odometry is obtained by matching consecutive laser scans to find the relative translation between acquisition poses [29]. To provide a single, more robust source of odometry, in this robot, we adapted an extended Kalman filter [30] to fuse these three different sources.

2.2. Manipulation

In the manufacturing sector, robotic applications are based on fixed automatons that repeat the same task over and over again with great accuracy. A different approach has been sought in our solution, based on flexible mobile robots with the ability to be collaborative. That way, operators can share their workspace with the robot without the need to include barriers.

Many tasks are not solvable through the use of a single robotic arm (i.e., Neobotics MM-700), such as manipulation of large objects, packaging, etc. Dual arm manipulation provides much greater flexibility but requires the ability to simultaneously solve the two arms' kinematics to achieve synchronous and smooth movements. Based on our previous research in this subject [31], a dual arm system composed of two UR10 collaborative robotic arms was chosen. With a payload of 10 Kg each arm, a combined payload of 20 Kg is achieved, greatly increasing the manipulation capabilities of the system, unlike other double-arm solutions such as the Baxter robot that are limited due to their low payload.

In a dual arm system, the relative position of both arms is a key issue. The relative position between arms must maximize the operational space while minimizing singularities. Thus, a study of the reach of the arms to know the volumes of joint work was done. As a result, it was found that the optimal way to fix the arms to the robot is by using an A-shaped pedestal instead of a V-shaped one (Figure 4).

To provide the robot with greater reachability and therefore increase the useful workspace, arms are mounted over a longitudinal axis in the frontal part of the robot. This vertical axis is also able to rotate, providing two additional degrees of freedom. Rotation covers ± 350 degrees of amplitude, allowing the arms to reach objects on the sides and on the back of the robot. The elevation axis has 670 mm of travel. This travel, provided by a threaded spindle, can raise the arms' base, allowing the TCPs to reach from ground level to a height of 2.5 m.

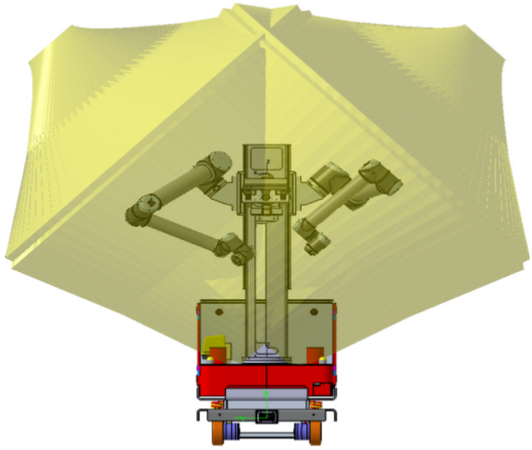


Figure 4. Arms reach volume.

2.3. Components and Systems

Endurance is another key issue in mobile robotics. While static robots are permanently connected to power, mobile robots rely on limited life batteries to operate, which should last enough to not interfere with the production process. Thus, a set of batteries able to work for a whole 8 h turn should be provided. A consumption study of all the electronic devices of the robot showed that a set of lithium batteries of 200 A/h should be enough for normal operation, with the possibility of doing opportunity charging while performing static tasks. Batteries are a big and heavy component, weighing about 80 Kg. They have been placed in the lower part of the robot in order to lower the center of gravity and increase the overall stability of the platform.

A small pneumatic system has also been installed in the MRP. This system is composed of a small compressor and a 5 L air tank. This system is enough to feed pneumatic tools fixed on the robot's arms and other pneumatic applications with low flow demand, like tool exchangers. For higher demand applications, compressed air can be provided trough a docking mechanism in the frontal part of the platform.

This docking mechanism allows a physical connection between the robot and an external entity. This system is a conical connector where the male part is in the robot and the female part is installed in one or several fixed positions where services (compressed air, power supply) are required by the robot. To avoid proper connection and avoid leaks, both parts must be attached tightly, which requires an accurate positioning of the robot. To successfully achieve this, a vision-based docking system was developed, as described in Section 3.2.1.

In addition to compressed air and power, the docking mechanism allows many other types of services to be passed through, such as digital signals, hydraulic systems, etc.

Flexibility comes from the ability to perform different tasks, which themselves usually require specific or even ad hoc designed tooling. It is, thus, necessary that the robot have the ability to autonomously change tools. The MRP is equipped with a pneumatic claw exchange system, with coupling male/female parts attached to each arms' last link and each of the tools. The opening and closing of these exchange systems is controlled by a set of solenoid valves, which can be commanded by the controlling software through Modbus.

Since many different tasks and tools are expected to be used, the robot is unable to carry all the required ones. Thus, tools are stored either in a dedicated tool-warehouse area or in the same workspace where the task is to be performed. Thus, the robot needs to detect the position of the required tools when arriving to a specific workspace. A fiducial-tag-based vision system is used to detect the tool stand and perform the tool exchange. Thanks to the skill-based programming system [32], the MRP knows which tool to select in each task.

2.4. Perception and Safety

Versatility requires perception of a dynamic environment surrounding the robot. For that, the robot is equipped with a variety of sensors of different nature and purpose. Beyond the internal encoders and IMU, the robot is equipped with:

- Two Sick S300 safety laser scanners mounted on opposite corners of the base;
- Two Roboception rc_visard stereo cameras mounted on the arms;
- One Microsoft Kinect 2.0 mounted at the top of the elevation column;
- One Intel RealSense D435 mounted on the robot arms' base;
- Two IDS uEye GigE cameras mounted at the front and right side of the base;
- Force torque sensor ATI Delta.

Safety is a critical issue when a shared human–robot workspace is wanted. Thus, the robots must be equipped with adequate safety sensors and measured, in compliance with current regulations. The installed safety lasers cover the entire perimeter of the robot and are attached to a safety rely that breaks the platform and the arms in case of invasion of the defined safety zone. Additionally, the robot has four safety buttons and an additional safety remote that acts the same way.

3. Autonomous Navigation

The capacity to autonomously navigate the work environment is one of the main differentiation points of AIMMs with respect to more traditional industrial robotics.

In our approach, two levels of navigation have been identified: long-range, rough navigation (which in a more practical way we call *cell-to-cell* navigation) and short-range, accurate navigation (which we call *in-cell* navigation).

3.1. Cell to Cell Navigation

To allow this concept of flexibility in production, it is necessary that robots have the ability to move between different working cells along the workshop, in order to perform as many different tasks as possible. This navigation usually covers relatively long distances in big environments. Further, accuracy in the positioning is not a key issue, usually being in the range of decimeters. Safety and trajectory efficiency are considered more relevant factors.

Laser-based 2D navigation is a mature and well-established technology [33] that is well suited for a traditional industrial workshop. Thus, the approach followed in this paper is that of using state-of-the-art 2D navigation techniques, augmented with the fusion of 3D information provided by additional sensors to cope with some of the limitations of traditional purely 2D approaches. Implementation details are provided in Section 3.1.4 of this paper.

3.1.1. Laser-Based Navigation

The base navigation of the MRP is composed of standard 2D laser-based navigation. Several implementations available as packages of ROS have been configured, tested, and fine-tuned for the mobile robot. This 2D navigation is used as a base system for global and local navigation.

Standard laser-based navigation is typically composed of a two-step approach:

In a first learning step, a simultaneous localization and mapping (SLAM) [34,35] is used to generate a 2D occupancy map. The implementation tested and used is the SLAM approach from [36], available in ROS as the package *hector_mapping*. The main advantage of this approach is that it offers great robustness without depending on additional ego-motion estimation sources (e.g., odometry). One of the key tasks performed for the implementation of the navigation in the MRP has been to fine-tune the algorithm for its specific dynamics.

In the second step, the already learned map is used for navigation. This navigation is also composed of two levels:

- **Localization**: This module provides a position based on the already recorded map. The localization algorithm used in THOMAS is the well-known augmented Monte Carlo localization (AMCL) from [37], available as the popular AMCL ROS package [38]. AMCL is considered as the de facto standard for laser-based localization and is widely used in many applications;
- **Planning**: This module is for both computing safe paths for the robot to travel and send direct speed commands to the drive controller to allow the robot to follow that path. This planning is also made at two levels:
    - **Global planner**: This module is responsible for computing a complete path from the starting point to the goal point. This computation is purely geometric, based on the well-known Dijkstra [39] and A* algorithms. ROS provides implementations for both algorithms in the packages *global_planner* [40] and *navfn* [41], available as plugins of the ROS navigation stack. Both have been tested, *global_planner* being the one normally used;
    - **Local planner**: This module is responsible for two tasks: On the one hand, it computes actual speed commands to follow the planned path, and on the other hand, it adapts the previous path to avoid obstacles in collision course, not present when the original path was computed. There are several packages available in ROS that implement different algorithms and approaches for this task. Three of them have been tested with the MRP, with different outcomes:
        * **dwa_local_planner**: This ROS package [42] implements the classic dynamic window approach (DWA) from [16]. It is a robust and well-proven algorithm. However, the generated trajectories for an omnidirectional robot are somehow very unintuitive for a nonknowing human observer. Since the intended use of the MRP is in collaboration or close by with humans, this approach was abandoned in favor of more modern approaches that allow for better behavior adjustment;
        * **eband_local_planner**: This module [43] uses an elastic band approach, generating bands (curves) that link consecutive points in the path, as described in [44] While obtaining good paths, its current implementation is focused on differential drive robots, so very often, the generated trajectories do not take advantage of the omnidirectional capabilities of the platform;
        * **teb_local_planner**: This package [45] implements the timed elastic band (TEB) approach [46], which tries to optimize the original trajectory with bands that minimize the trajectory execution time, separation from obstacles, and compliance with the kinodynamic constraints. It is the newest approach from the three and allows for greater configuration and fine-tuning of the final behavior. Since the Kinetic ROS version, it implements support (later backported to Indigo version) for omnidirectional robots. A great effort has been dedicated to tuning the planner for the MRP's specific dynamics. As a result, this by itself allows for safe and robust navigation, as was shown during the Bienal Maquina Herramienta (BIEMH 18) (The Spanish machine tool biennial is the third most important industrial fair in Europe and the first of its sector in Spain. It is held

every two years at the Bilbao Exhibition Center (BEC) in Barakaldo, aimed at the main manufacturers, importers, and distributors of machinery and robotics, inviting them to exhibit their products and reach trade agreements with the more than 35,000 buyers in the main countries of the world), where is was part of a demonstrator that was working continuously for 10 h, for 5 consecutive days. However, it still presents some issues in very cluttered environments, in which proximity from obstacles and noise in the sensors cause instability in the generated optimal paths. This, combined with the slow reaction to orientation changes of the MRP due its swerve drive, sometimes results in in very slow speeds.

3.1.2. Low Level Wheel Management

As described previously, the mobile platform is a four-wheeled, omnidirectional platform in the configuration usually referred as "Swerve drive". The Swerve drive is composed of several (usually four) wheels that can be controlled both in orientation and speed. Each configuration of wheels with their orientation and speed provides a specific linear and angular speed to the center of the platform (Figure 5), providing three degrees of freedom.

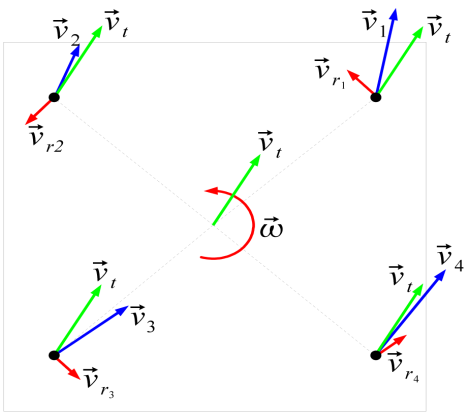


Figure 5. Relationship between each wheel's speed vector and platform's speed vector and angular speed in the Swerve drive configuration.

The Swerve drive is frequent in omnidirectional platforms since it has several important advantages, such as that it uses simple wheels (that provide better stability) and has greater pushing force (since all wheels provide traction).

However, it also has some important drawbacks, coming mainly from the complexity of its control scheme and build. It has an inherent limitation, since it needs to reconfigure the four wheels to be able to change a robot's traveling direction. This forces the robot to either stop and reconfigure the wheels or continue while dragging the turning wheels. This problem is more evident in robots with limits in the turning travel of the orientation wheels and with low wheel turning speeds, as is the case with the MRP.

In the case of the industrial application which we tried to automate, a smooth platform movement is a requirement since it combines platform movement with manipulation (e.g., dumper screwing in the automotive use case). Many stop-and-reconfigure motions were not possible due to the nature of the application, as stated. Dragging the wheels was also problematic due to the weight of the platform (putting a lot of stress in the dragging wheels) and the vibrations it creates (propagated to and increased in the arms' tips).

Thus, the wheel management part of the swerve drive we implemented in the MRP was specifically tuned to adequately balance both possibilities. Three different elements were adjusted:

- Maximize the allowed travel of the orientation wheels, keeping the minimum distance to the physical limits that safety allows;
- Tune the reorienting of the wheel vs. inverting its speed strategy, taking into account the driver's speeds and acceleration ramps. This management is critical in platform orientation changes, when the new desired orientation of the wheel is far from the current position, as it can be less time costly to invert the traction wheel and orient the wheel at 180° from the original target. The extreme case is when the platform's traveling speed between moving forward and backward is inverted: It is less time-expensive to not reorient the wheels, but to just invert their traction speed, keeping the orientation;
- Set an acceptable level of dragging (i.e., the maximum difference between target and current wheel orientation to trigger a stop-and-reconfigure action). In the case of the MRP, this difference was set experimentally at 15°, as no apparent vibration was propagated to the robot at that dragging level.

Finally, the wheel drivers where also finely tuned to adapt them to the specifics of the MRP and its control system.

3.1.3. Dynamic Robot Footprint

To safely travel the environment, the robot not only needs to know the available space and the position of the obstacles surrounding it, it also needs to be aware of what amount of space itself occupies to know in what positions it can stand in without colliding with any other object in the environment. Traditionally, this space that the robot occupies is known as the robot's "footprint".

In 2D navigation approaches, the footprint is estimated as the projection (the plant) of the robot in the map's plane. A conventional robot usually has a fixed footprint, and current available approaches do not consider the possibility of a robot with a changing form.

This is not the case in a mobile manipulator. This kind of robots are equipped with robotic arms that can project over the base footprint and whose configuration changes over time. Since the navigation system is not aware of this, it creates a situation with high collision risk (e.g., the navigation system tries to go through a door which the base can traverse, but the arms not).

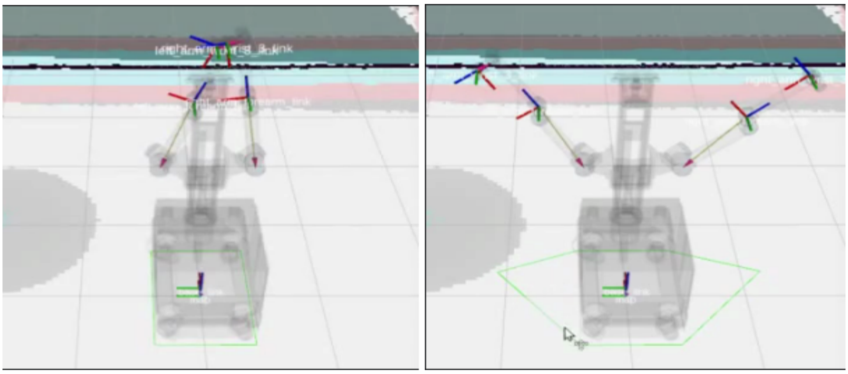
Traditionally, this problem is dealt with by defining a safe travel arm configuration in which arms do not project over the mobile base limits. Every time the robot needs to move, the arms must be put in the travel configuration. This notably increases cycle times and prevents any simultaneous navigation and manipulation.

To avoid that, a new module for dynamic footprint adaptation was developed and is presented in this paper. This module has three functions:

- Monitor the arm's joints to obtain their position with respect to the robot's base;
- Compute the bounding polygon of the most external joints and base borders;
- Replace the current footprint with the computed bounding polygon.

Additionally, the standard ROS planner used for navigation has been modified to work with changing footprints, instead of using a fixed one from the start of the execution.

An example of the use of this module can be seen in Figure 6, where in the left there is the "standard" footprint covering the mobile base, while in the right, the footprint has been extended to also cover the stretched arms.



(**a**) (**b**)

Figure 6. (**a**) Default footprint (green line) covering the MRP's base. (**b**) Updated footprint covering the stretched arms.

3.1.4. 2D Navigation Improvements by 3D Perception Fusion

As mentioned before, 2D-laser-based navigation is the current state-of-the-art navigation approach for indoor structured environments. The use of the "plant" of the environment as a map is a well-known, widely-used, and robust method for localization and navigation. It also has, however, some well-known limitations, such as its sensitivity to ambiguity in very symmetric environments.

Safety-wise, there is one critical issue that arises by the same nature of the environment representation that the system uses. The "known world" is limited to what the robot's sensors can see and what can be represented in the map. In the typical laser-based navigation, this is limited to obstacles in a plane at the height at which the laser scanners are mounted. This causes obstacles above and below this plane to be invisible to the robot.

In a typical structured environment, most of the existing obstacles do not pose a threat, since they typically have flat vertical surfaces and go from the ground to some height. Thus, a low-mounted laser can safely detect most of them. However, protruding and hanging obstacles, tables or very low obstacles like pallets still pose a safety threat. One typical and especially dangerous case are the feet, since they can easily project 20–30 cm from the leg (which would be what the robot actually detects) and can be run over even when the robot has detected the person, depending on the robot's safety configuration.

A full 3D localization/navigation system should be able to overcome these problems. However, the current state of 3D navigation is not so developed and well tested as 2D navigation, so any intent of using such technology will require longer development times with much more uncertain results. Alternatively, standard 2D navigation can greatly benefit from the use of 3D information sources, while retaining its well-known robustness.

3D Perception Source

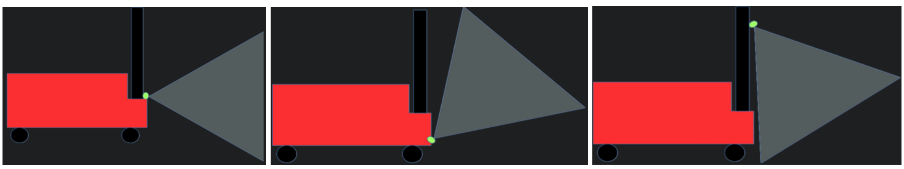
Multiple possibilities exist for providing 3D information for use in the navigation, both on-board and off-board the MRP. The robot is already equipped with several 3D able cameras, such as the Kinect installed in the torso of the robot and the rc_visard cameras from Roboception. These cameras, however, require a pattern to be projected to be able to get 3D information, so they were discarded for navigation purposes as they would require the projector to be constantly lit.

Alternatively, an Intel RealSense D435 3D camera was mounted on the MRP instead of the Microsoft Kinect due to the fact that the Intel camera has a better resolution and sensor quality.

As the vertical field of view of the camera is limited, how the camera is mounted pn the MRP is relevant to its usefulness for obstacle detection. Basically, three options were possible:

(a) Horizontal mounting: This would be the most standard mounting. However, die to its limited field of view, the camera would only detect obstacles far away from the robot. That will limit its usefulness, since, while the detected obstacles would be used for global navigation, only close obstacles are relevant in the local navigation and are more relevant for safety;
(b) Tilted mounting at low height: A camera mounted this way would be able to detect close-by obstacles at all the height of the robot. However, it has the same problem as the lasers, as it would not be able to detect very low obstacles;
(c) Tilted mounting at high height: It can detect close-by obstacles from its mounting point to the ground. Available mounting points in MRP are high, so it was considered that this mounting would be the one with the greatest obstacle detection capabilities. Its main drawback is the need to filter the ground from the generated point cloud.

Final mounting has been done in the auxiliary plate between the two dual arms in the MRP's torso, pointing down 60° degrees, as shown in Figure 7c. The camera has been manually calibrated so the acquired point cloud has been properly acquired with respect to the robot. To improve performance and reduce noise, the ground has been removed from the point cloud up to a height of 1 cm.



(**a**) (**b**) (**c**)

Figure 7. Three different mounting positions of the camera on the robot. (**a**) Horizontal mounting, (**b**) Tilted mounting at low height, (**c**) Tilted mounting at high height.

It needs to be considered that a single front-mounted camera has limited functionality in an omnidirectional platform for navigation purposes. It is only able to detect obstacles in front of the robot, whereas the robot can, and usually does, movements backwards and sideways. As it is done with the laser scanners, a fully practical installation requires multiple cameras covering 360° around the robot. On the MRP prototype, only one camera is being used for testing purposes.

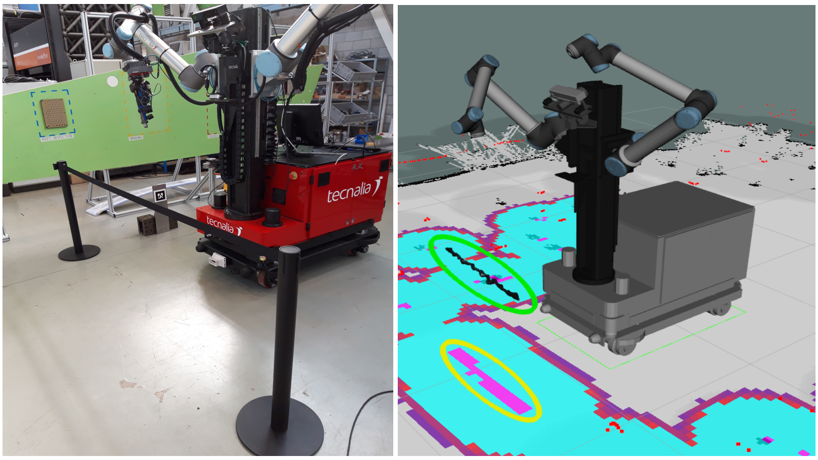
3D Obstacle Detection

The 3D information (point cloud) provided by the 3D camera is used for the detection of 3D obstacles.

The point cloud feeds a new layer in the costmap (occupancy grid) used by the navigation. In this layer, instead of using a single, planar cell to represent each map position, a column of voxels is defined. If the position of points in the cloud falls within the voxel, the voxel is marked as occupied. Then, this voxel column is flattened, giving the highest occupation value in the voxel column to the corresponding cell in the navigation map. In this way, any position in the map would be marked as occupied even if the obstacle occupying it is above or below the plane of the laser scanners.

Once the costmap is updated with the 3D sensor information, this information is seamlessly used by the navigation stack, thus allowing the robot to avoid previously invisible obstacles.

Figure 8 shows and example of how a stanchion barrier, which is an obstacle well above the laser height, is successfully detected and projected to the costmap.



(**a**) (**b**)

Figure 8. 3D obstacle detection. The barrier in front of the MRP (**a**) is detected (highlighted in green in (**b**)) and projected in the obstacle map (highlighted in yellow).

3.1.5. 3D-Perception-Based Navigation

Most commonly used navigation systems rely on laser sensors (e.g., lidar) to calculate the distance to obstacles. As opposed to the classical approach that uses laser sensors as the main input to tackle this task, visual SLAM algorithms use vision sensors to solve the same problems. There are some advantages to using vision sensors in relation to solve the same task with laser sensors:

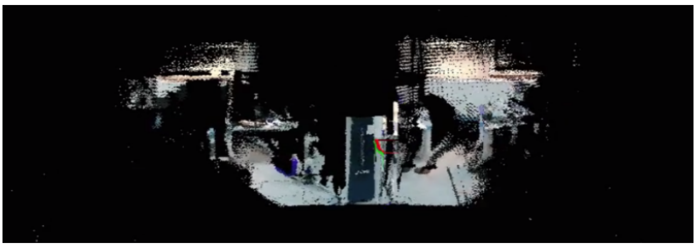
- Sensor consumption/cost: Vision sensors are typically cheaper than lidar sensors and consume less power, which has an impact on the autonomy of battery-powered mobile robots;
- Re-localization: This relates to both the problem of initialization and the problem of recovering the robot's localization once the tracking is lost. Vision sensors provide richer information and allow solving this problem in a more efficient way;
- 3D obstacles: Lidar sensors typically provide distance readings in a scanning plane (there are exceptions that provide scanning movements in two axis). This can potentially lead to collisions in case some obstacles cannot be correctly detected;
- Map information: The amount and quality of information provided by a sensor system is much richer, which can be used to produce richer maps.

However, it is important to note that we do not propose to substitute laser sensors with vision. Laser provides very robust readings and allows for safety certification to be achieved, while vision sensors are much harder to certify. We propose to combine both sensor modalities, as it is a good way of improving a system's robustness and resilience to have redundant information coming from different sources with different parameters of performance and failure modes.

To perform the initial tests, we reviewed the state-of-the-art of visual SLAM methods [47,48], focusing on those with open implementations provided, in order to minimize the integration time required.

After examining more than 20 algorithms and classifying them under different criteria (type of sensor used, type of map created, relocation capability, GPU vs. CPU, and many others), we finally chose the RGBDSLAMv2 algorithm for the initial tests, as it provides very good integration with ROS and has a clean code structure that can be modified. In order to avoid conflicts, we decided to use a Docker-based solution. Docker provides isolation from dependencies in the system, while avoiding any performance penalty as in the case of virtual machines.

Out of the initial tests performed, Figure 9 shows the initialization of the system. Figure 9a shows the map created, which is represented as a pointcloud. The library offers functions to export the pointcloud to an octomap, which can then be used by other ROS packages to, for example, perform a path planning. Figure 9b shows the initial 2D color image getting from the sensor. In turn, Figure 9c shows the depth obtained thanks to the laser that incorporates the sensor. Figure 9d shows the features located in the 2D image that are used to calculate the camera tracking.



(**a**) vSLAM first pointcloud

(**b**) 2D color image (**c**) Depth image (**d**) Points of interest

Figure 9. Visual simultaneous localization and mapping (vSLAM) initialization view.

Figure 10 shows the map produced after a run in the test environment, with the camera/robot trajectory.

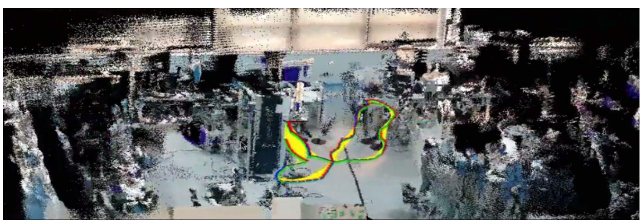


Figure 10. Final 3D map of the environment and robot trajectory.

3.2. In-Cell Navigation

Once in the working cell, an AIMM has to perform a task. Usually, this task is a manipulation that requires high position accuracy to be successful. While standard approaches used in cell-to-cell navigation are good enough for obstacle avoidance and to approximately approach the desired position goal, it is not accurate enough for other tasks. Thus, as a way to achieve this final, accurate positioning, a visual docking mechanism has been developed. Moreover, the use cases include a scenario with a "mobile workstation" in which the MRP needs to perform a screwing operation on the parts that a moving mobile product platform (MPP) is carrying. A mobile "virtual" docking mechanism also has been developed to track and keep a relative position with respect to a mobile goal.

3.2.1. StaTic Docking: Accurate Positioning with Respect to a Static Reference

As described before, the MRP's internal pneumatic system is only able to provide enough air pressure flow for a few seconds. Thus, it is required that the MRP must attach itself to a docking station that provides enough airflow. This docking procedure required high positioning accuracy, which would also be required by the operations themselves (drilling pattern detection, self-positioning against the wing in sanding processes, etc.).

A fiducial-based visual servoing docking system was developed and tested. The system is based on a proportional control that maintains and ensures, with the desired tolerance, the position of the robot with respect to the marker. To obtain a good response and fluid movements of the robot, a closed loop system with a sampling frequency of 20 Hz is used. Instead of directly using the estimated error in the image, a frame transformation is performed to validate the position and orientation from the detected marker from the camera reference to the base of the robot. This makes the system agnostic of the mount point of the tracking camera.

The position error between both is translated, within a closed loop, as setpoint speed that is sent directly to the robot's traction system. The system accepts various configuration parameters to achieve precise docking, like maximum speed and goal tolerances. The reference goal was recorded in a previous calibration process. The system allows for both approach (dock) and walk away (undock) from the reference.

Initial validation of the system was done with the mounted Microsoft Kinect, but is showed some limitations that required a large marker. To solve this, a high-resolution IDS camera was installed in the front of the robot's base. This improved greatly image quality and accuracy, allowing the use of a much smaller marker, less invasive with the working area. This marker was attached to a docking and charging station able to provide compressed air and power (Figure 11).

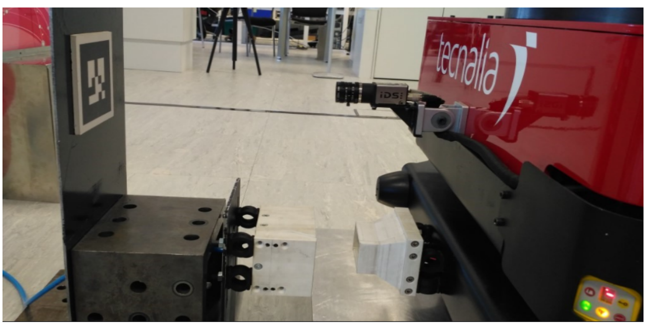


Figure 11. Final docking system with an IDS camera, charge station, and marker installed.

3.2.2. Dynamic Docking: Mobile Reference Accurate Positioning and Trajectory Following

In-cell navigation in the automotive use case requires the synchronized navigation of the MRP and MPP. While the developed static docking is robust and accurate, it is not designed to track and follow a moving target. Thus, a different system was required for this task.

Perception

Initially, a sensor fusion system using the on-board Microsoft Kinect and the laser scanners was proposed. This approach tried to combine the accuracy of the marker based tracking with the speed of laser scanners. The literature shows many examples of laser based detection and tracking of objects, such as people and vehicles in outdoor conditions [49], or combining SLAM with tracking of moving objects (DTMO) [50]. The basic approach is to match the "shadow" created by the objects in the laser readings [51]. Detection and tracking of the MPP would be done by fusing the information of the lasers with the image coming from the camera, as seen in Figure 12.

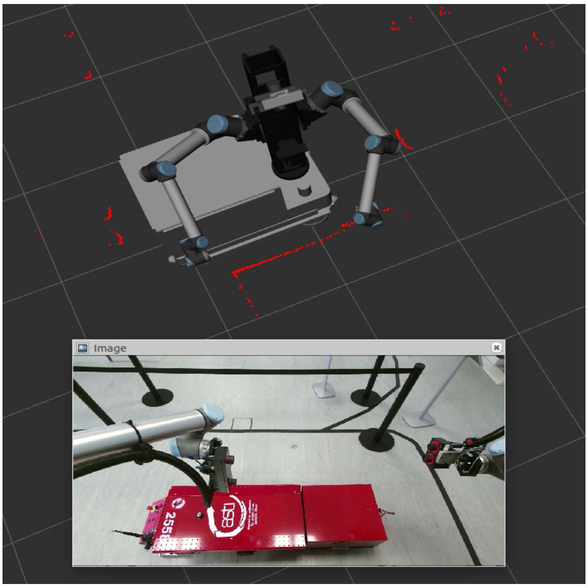


Figure 12. Silhouette of the MPP viewed from the MRP's laser scanners and correspondent camera image.

Initial tests, however, showed that the head, pan-tilt mounted Kinect camera was not accurate enough for the task, due to the big minimum distance to the target marker, low camera resolution, and difficult calibration of the kinematic chain encompassing the robot's base, torso and pan-tilt unit.

Similarly to the final configuration of the static docking, an industrial IDS uEye GigE camera was mounted on the robot's side at low high. This mounting point allowed placing the tracking marker on one of the "legs" of the MPP's dolly where it both allowed a very close tracking distance (50 cm) and a good position of the torso and arms over the dolly for manipulation tasks.

The fixed mount, high resolution, and close tracking distance provided very good tracking accuracy. Moreover, the camera and tracking system were able to provide up to 30 fps. This speed made the fusion of lasers for increased tracking speed unnecessary.

Control

As the goal of the application is to be able to perform some manipulation in the parts carried by the MPP's dolly, the target of the tracking system is to maintain formation with the MPP. As the union between the MPP and the dolly is not rigid, a steady relative position to the dolly (and not the MPP) should be kept.

While the MPP's movement is linear in most of its trajectory, the dolly's movement is more erratic, oscillating depending on different variables, such as the initial position of the wheels or the conditions of the ground.

Thus, control of the MRP should be done in the three possible degrees of freedom: lineal, lateral, and angular speeds. Since the dolly's movements in each dimension were expected to be very different, each speed component was controlled with its own PID with different gains. This way, for instance, linear PID had much higher reactivity than the lateral or angular ones.

PIDs were fine-tuned via multiple repetitive testing in our workshop, as can be seen in Figure 13.

Figure 13. MRP following the mobile product platform (MPP) through the dynamic docking (visual servoing) system.

The achieved accuracy was in the order of <1 cm once the following stabilizes, which takes approximately two seconds. This error should be mechanically absorbed easily by the arms or tooling.

However, at the start, the error can get as high as 4 cm. This initial high error is inherent to the reactive nature of the feedforward PID and the dynamic reactions of the MRP (command-to-action delays, acceleration ramps, etc.). The initial error can potentially be greatly reduced if the system is able to command both the MPP and MRP to start simultaneously, instead of the MRP to be waiting for the MPP to start moving. Unfortunately, this capacity required some equipment from the AGV provider that was not available at the time of development, but it should be studied in further developments.

4. Process Control and Programming

4.1. Skill-Based Programming

Skill-based programming has been used in this robotic solution [52]. Each skill represents a singular operation or task (detect one part, move arm to a pose, grasp, etc.) Encapsulated in skills, each task acquires a higher level of abstraction, making it easier to manage the flow of execution and making the system more robust to changes and errors in the processes.

Skills can be combined to generate more complex skills to create specific solutions that solve new problems. This skill-based approach reduces the time devoted to programming and allows the reuse of the skill learned in other similar processes. A graphical user interface (GUI) has been developed for the management of skills, as can be seen in Figure 14.

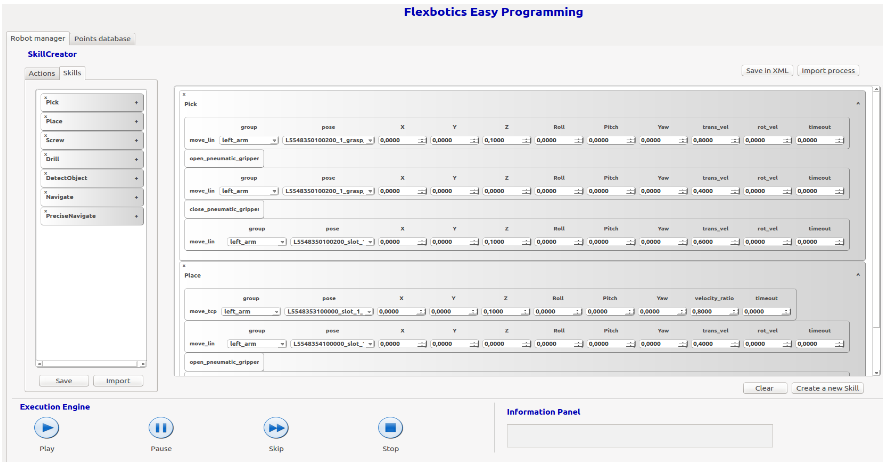


Figure 14. Graphical user interface (GUI) developed for skill management.

4.2. High-Level Task Management and World Model

As part of the THOMAS project, the MRP is integrated into a more complex system ideally composed of several MRPs and a higher-level task management system [53]. A world model also allows for seamless exchange of environment information between different agents (robots, sensors, operators) in the workshop [54].

5. Results

The performance of the proposed system was evaluated through a series of tests.

5.1. Static Docking

Static docking is used to accurately position the MRP to perform tasks where there is a very low tolerance for a positioning error. Two cases are present in the proposed scenarios: to detect and align against the MPP in the automotive use case and to connect the robot to the pneumatic pressure through the docking mechanism in the aeronautics use case.

A set of tests were performed using the proposed system and without using it (i.e., with the final position given by the cell-to-cell navigation). The number of successes was sought, with a test being considered a success when the final position is accurate enough for the MRP to be able to continue with the next skill in the task. In the case of the Aeronautics, it would be if the external pneumatic system is properly connected, allowing the operation of the ADU. In the the Automotive use case, it would be if the MRP is able to start following the MPP.

A total of 60 tests were carried out within the Tecnalia facilities, which has a mixed illumination of large windows and artificial light.

As can be seen in Table 3, in cases where static docking was used, the robot was able to continue performing its next skill without problem in 96% of the attempts. The recorded failure can be possibly attributable to the reflections of the sunlight on the marker, making the camera unable to detect it.

When not using static docking, in the case of aeronautics, the MRP was unable to insert the docking mechanism in every attempt, thus being unable to activate the ADU. In the case of automotive, the MRP was able to follow the MPP in most of the tests, due to the lesser positioning requirements of the tracking system. However, the initial tracking error was very big, requiring a longer tracking stabilization time and greatly reducing the time available for the screwing operation, making it almost impossible to achieve.

Table 3. Comparison between the results of using or not using the static docking system.

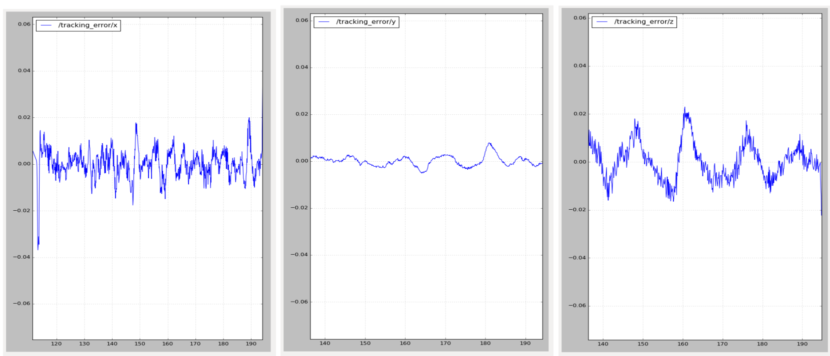
	SLAM + Static Docking		**Only SLAM**	
	Automotive	**Aeronautic**	**Automotive**	**Aeronautic**
Sunrise	5/5	4/5	4/5	0/5
Noon	5/5	5/5	4/5	0/5
Sunset	5/5	5/5	5/5	0/5
Subtotal	15/15	14/15	13/15	0/15
Total	**29/30**		**14/30**	

5.2. Dynamic Docking

In the case of tracking the MPP through the use of the dynamic docking system, the tests were carried out by performing a prior static docking to guarantee an accurate and repetitive initial tracking position error.

Multiple tests were performed to adjust the parameters of the three PIDs until a valid configuration was obtained for the purpose of screwing on the MPP. Twenty tests were recorded to quantify the values between which the error fluctuates.

Figure 15 is an example of one of the records, where error in longitudinal (Figure 15a) and lateral (Figure 15b) distances and angular error (Figure 15c) are plotted.



(**a**) Longitudinal error (**b**) Lateral error (**c**) Rotation error

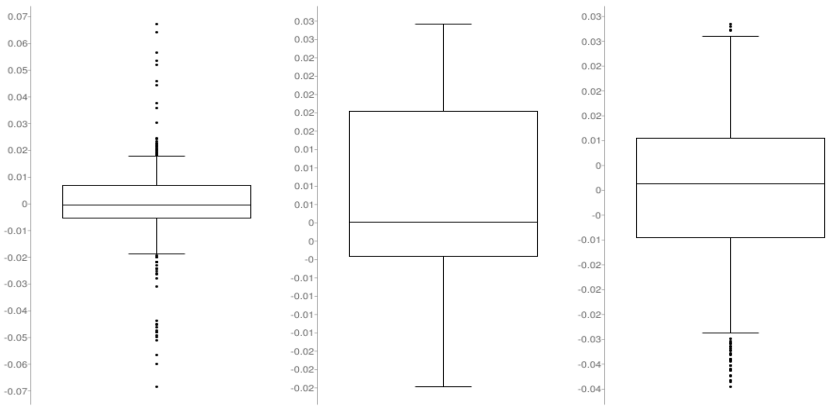
Figure 15. Dynamic docking—tracking error expressed in centimeters between MRP and MPP.

It can be easily appreciated in the left graph that there is a big initial longitudinal tracking error due to the delayed reaction of the MRP when the MPP starts moving. This error is quickly corrected by the dynamic docking system in about 2 s, when the error becomes stationary around ± 0.015 m.

As can be seen in Table 4 and Figure 16, the maximum and minimum longitudinal errors never exceed 7 cm, corresponding with the mentioned initial error. The first and third quartiles show that most of the time, the error is less than 1 cm, with a mean absolute error of 9 mm. In the case of lateral error, which is not so critical, the mean error is a bit higher. Smooth corrections were prioritized against quickly reducing the error. A relatively high median (that should be very close to zero) shows a bias in the robot's behavior, keeping it a bit further away from the goal than desired. The angular error is very low overall.

Table 4. Results obtained in the dynamic docking tests between the MRP and the MPP. Error in longitudinal (m), lateral (m), rotation (rad).

	(a) Longitudinal Error	**(b) Lateral Error**	**(c) Rotation Error**
Mean (abs)	0.00908	0.01069	0.01232
Median	−0.00041	0.00264	0.00124
Lower value	−0.06834	−0.01981	−0.03949
Higher value	0.06719	0.02957	0.03342
First quartile	−0.00544	−0.00210	−0.00953
Third quartile	0.00675	0.01776	0.01052



(**a**) Longitudinal error (**b**) Lateral error (**c**) Rotation error

Figure 16. Dynamic docking—results expressed in quartiles.

5.3. General Results

The docking system proved to be robust, being able to achieve docking successfully from almost any position, given that the marker is in the field of view of the docking camera. The only drawback found was, with it being a vision-based system, a sensitivity to extreme lighting conditions.

The navigation solution was showcased in real live in three demos. A public demonstration was made as part of the Open Doors day organized by the EU Robott-net project [55] in San Sebastian's Tecnalia premises. The second occasion was the THOMAS integration workshop done at the Laboratory for Manufacturing Systems (LMS), in which the in-cell navigation static and dynamic docking was integrated into the LMS's second prototype of the MRP. The implemented software system has proven robust when deployed on other robots with different sensors that were tested during development.

Finally, a demonstrator was shown in the BIEMH18 fair, where the MRP was in continuous operation for 5 days, 10 h per day, as mentioned earlier.

Given its robustness, the developed systems are already being used in other projects with AIMM applications with similar needs, like the EU Versatile project [56].

6. Conclusions and Future Work

In this paper, we have presented an innovative AIMM design, the MRP used in the project THOMAS. Details of the motivations of the design decision making were provided, as well as the solutions finally adopted.

Several systems of the MRP have been also presented.

The cell-to-cell navigation system is in a good shape, as demonstrated in different tests, such as the BIEMH 18 fair, and 2D navigation was improved through the fusion of 3D sensors information that allows for the detection of obstacles beyond the plane of the laser scanner, improving system safety. The fusion of full 3D navigation is expected to add more robustness in more symmetric and open spaces.

In in-cell navigation, a docking base module was developed. An AR marker was used to self-locate with respect to a precalibrated relative position. The estimated relative position of the marker was translated to control movements. Static docking has shown to be robust and accurate. The big challenge in this area is mobile docking. The performed tests suggest that achieving a reasonably robust and accurate enough mobile docking is envisioned to be possible. However, depending on the nature of operation, the MRP should perform synchronized with the MPP, and it could be necessary to add additional hardware in the arms to physically compensate the remaining error.

The current system navigation capabilities and robustness have been demonstrated in several demos. Further, both static and dynamic docking perform robustly, with only a problem found in extreme lighting conditions.

One of the main identified problems for mobility is the dynamic response of the motorwheels in a complex control scheme like the Swerve drive. As future work, an analytical tool [57] can be used to optimize drive control.

Further developments will be mainly focused on the integration of the systems in the full-scale use of a case demonstrator.

In cell-to-cell navigation, only a few tweaks are expected to be needed, and most development will be devoted to integration of new sources of sensor information (off-board sensors, world model). Full 3D navigation fusion will remain as a less immediate possible improvement.

In in-cell navigation, most of the required work is expected to be done in dynamic docking, trying to improve its accuracy as much as possible to be able to successfully perform the screwing process.

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Abbreviations

The following abbreviations are used in this manuscript:

ADU	Automatic Drilling Unit
AGV	Automatic Guided Vehicle
AIMM	Autonomous Industrial Mobile Manipulator
AMCL	Augmented Monte Carlo Localization

BIEMH	Bienal Española de Máquina-Herramienta
DOF	Degree of Freedom
GUI	Graphical User Interface
IMU	Inertial Measurement Unit
LIDAR	Light Detection and Ranging
LMS	Laboratory for Manufacturing Systems and Automation
MPP	Mobile Product Platform
MRP	Mobile Robotic Platform
RGBD	Red Green Blue Depth
ROS	Robot Operating System
SLAM	Simultaneous Localization and Mapping
TCP	Tool Center Point
TEB	Time Elastic Band

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A real application of an autonomous industrial mobile manipulator within industrial context

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A Real Application of an Autonomous Industrial Mobile Manipulator within Industrial Context

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Abstract: In modern industry there are still a large number of low added-value processes that can be automated or semi-automated with safe cooperation between robot and human operators. The European SHERLOCK project aims to integrate an autonomous industrial mobile manipulator (AIMM) to perform cooperative tasks between a robot and a human. To be able to do this, AIMMs need to have a variety of advanced cognitive skills like autonomous navigation, smart perception and task management. In this paper, we report the project's tackle in a paradigmatic industrial application combining accurate autonomous navigation with deep learning-based 3D perception for pose estimation to locate and manipulate different industrial objects in an unstructured environment. The proposed method presents a combination of different technologies fused in an AIMM that achieve the proposed objective with a success rate of 83.33% in tests carried out in a real environment.

Keywords: autonomous industrial mobile manipulator; deep learning; robotics; perception; sensor fusion; autonomous navigation; computer vision; skills; state machine

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1. Introduction

Industrial processes have undergone a number of transformations and improvements, from the early manufacturing processes of the previous centuries to the present day, achieving high levels of efficiency and automation. As Nye [1] describes in his work on the comparative review of 100 years of industrial evolution, today's assembly line "in a new way is more productive than ever", thanks to robotics.

Nevertheless, many low value and repetitive processes are yet to be automated [2]. This lack of automation in certain tasks, usually performed by low-skilled operators, has been caused mainly by the cost of replacing low-wage operators with expensive automation systems that require very invasive changes in the area and a long reprogramming time by qualified specialists. In addition, replacing low-skilled operators with high-skilled ones is difficult and expensive. Newer education paradigms [3] have focused on the training of these high-skilled operators. However, the fast technology development and an aging workforce makes it difficult to maintain a proper high-skilled crew. This requires new solutions to assist operators and provide collaborative work environments [4]. It is expected that this successful transformation could ensure that robotics and autonomous transportation are able to create a global job growth of 1.36% [5].

The rise of autonomous systems and robotics, especially collaborative robots, is opening new market possibilities. A new trend for flexible and collaborative robotics is spreading in the industry in the form of autonomous industrial mobile manipulators (AIMM) [6]. These hybrid systems combine two widespread and mature technologies:

manipulation by robotic arms and mobile robotics. These capabilities are merged and improved with innovative techniques of artificial perception so that the robot has greater autonomy and decision-making capabilities.

These types of autonomous systems are fitted to the new industrial paradigm that has been in development in recent years: the fourth industrial revolution or "Industry 4.0". This term became publicly known in 2011, when an association of representatives from the business, political and academic world promoted the idea as an approach to strengthen the competitiveness of the German manufacturing industry [7]. In this paradigm, manufacturing and logistics processes take the form of cyber–physical production systems (CPPS) which make use of information and communications networks to interchange large amounts of information. Since its emergence, the concept of Industry 4.0 has attracted lots of attention and research [8] and numerous academic publications, practical articles and conferences have discussed this topic [9]. Similarly, the industrial robots manufacturing industry has adapted to this new approach, and in Europe alone the number of advanced robots developed almost doubled between 2004 and 2016 [10]. Among these new advanced robots, we can classify the previously mentioned AIMMs that are in the center of this report.

In a dynamic manufacturing environment, both the working areas and the manufacturing process itself are constantly changing. Thus, autonomous systems must be robust to changes. The environment perception and the capacity of readjustment must be fast and efficient.

The purpose of the work reported here is to provide a novel solution to one of the challenges proposed in the "co-manipulation of large aeronautic parts by dual-arm mobile manipulator" use case of the European project SHERLOCK [11]. This project aims to introduce the latest safe robotic technologies, including collaborative arms with high payload, exoskeletons and mobile manipulators in various production environments, enhancing them with intelligent mechatronics and AI-based cognition. The result will be creating efficient human–robot collaboration (HRC) stations that are designed to be safe and ensure the acceptance and well being of operators. Another fundamental pillar of the SHERLOCK project is the transition from traditional robotics to the new Industry 4.0 paradigm, where robotics are more flexible, autonomous, collaborative and interconnected. Within the project, other works that support it have already been published [12–14].

The scientific and technological objectives of the SHERLOCK project are summarized as follows:

- Bring recent research developments to a real world application;
- Development of a soft robotics collaborative production station;
- Novel human-centered interaction, collaboration and awareness;
- Artificial intelligence enabled cognition for autonomous human–robot collaborative applications;
- SHERLOCK modules for the design and certification of safe HRC applications.

In this context, the work reported here focuses on the second and fourth objectives, aiming to solve the challenge of recognition and detection of the supports of long aeronautical pieces by means of artificial vision techniques and deep learning. This will enable the AIMM to be able to locate the part and grasp it safely for the task that is entrusted to it. For those objectives, a lot of emphasis will be put on bringing recent methods and techniques found in the literature to the real world, along with using the currently well established, state-of-the-art methods.

The paper is distributed as follows. In Section 1.1, the objectives to be achieved in this work are described. Section 2 introduces the global system, beginning with the presentation of the AIMM and its technical details, Section 2.1, followed by the explanation of the navigation techniques used Section 2.1.1. Section 2.2 describes the perception system used to detect the required objects. The depth learning method used is explained in Sections 2.2.1 and 2.2.2. The calibration methods used for both the robot camera and the gripper TCP are described in Section 2.3. The control of the process is presented in Section 2.4 which describes the programming based on skills and the control and management of these skills by means of a state machine. Finally, the experiment is defined in Section 3 and in Section 4 the results obtained in the tests carried out are displayed. The paper ends with the discussion and future work in.

1.1. Objectives

The objective of this work was for the robot to be able to autonomously carry out a sequence of tasks using a combination of different state-of-the-art technologies in a real work environment. This sequence of tasks represent a prototypical application in industry that AIMMs should be able to accomplish. To successfully carry out this task, the robot should possess the following skills:

- Autonomous navigation between different objectives;
- Precise navigation to ensure that the target position is good enough;
- Be able to perceive the environment and make decisions to adapt to it;
- Ensure that the task is carried out safely in a collaborative environment;
- A computer vision system able to detect and identify the desired object using deep learning techniques;
- Be able grasp or touch the centroid of the recognized object;
- High-level management of the tasks to be carried out as well as error management.

The advances made in the implementation of such skills in the SHERLOCK project AIMM will be presented in this report. The main contributions of this work are the successful implementation of the mentioned task, integrating and tuning different available techniques and methods in one system and bringing them to a real world application. In addition, a new RGB-D training dataset, using synthetic images from real industrial parts, has been compiled and will be made available.

2. System Description

2.1. Innovative AIMM

The robotic system used in this paper is shown in Figure 1. It is an innovative robot designed by the authors and presented in [15], where it was described extensively. As this system meets all the criteria established in [16], it can be regarded as an AIMM. As such, it consists of two main parts: a drive system and a manipulation system.

For the drive system, the kinematic configuration is based on the Swerve Drive approach [17], consisting of four motor wheels driven in translation and rotation by eight motors. While not truly holonomic, the Swerve Drive's omnidirectional capability gives the robot great versatility. The medium-sized wheels offer good stability and the capacity to overcome small obstacles and ground irregularities. The AIMM reaches a maximum speed of 3 m/s, although it is limited to 2 m/s by software for safety reasons.

For the manipulation system, current needs of the industry show that processes require to perform complex object manipulation tasks. To provide the robot with greater versatility and improved manipulation capabilities, it has been equipped with two Universal Robots UR10 robotic arms. In this way, not only the total payload is increased, but it also allows more complex manipulation strategies by means of coordinated movements of the two arms [18].

The arms are mounted on a rotating vertical axis at the front, providing two additional degrees of freedom to the robotic arms (670 mm of elevation and $\pm$350º of rotation). This way the AIMM greatly increases its reachability (up to 2.5 m high) and the volume of the working space.

Figure 1. The AIMM used to carry out the tasks of the presented industrial application.

The robot packs many specially customized features that differentiate it from common commercial mobile manipulators.

- Large 200 A/h lithium battery for full shift operation. Its location was also designed to lower the robot's center of mass and help stability.
- Small capacity on-board pneumatic system enabling the use of pneumatic devices attached to the arms and a coupling mechanism to connect to an external compressed air system for higher demand applications.
- A docking mechanism that allows a physical connection between the robot and an external station for high accuracy positioning and resource exchange (opportunity charging, compressed air, input/output signals, etc.).
- A pneumatic tool exchanger system, allowing the robot to change the arm's tool on demand for different tasks. For the manipulation task presented in this paper, a customized pneumatic gripper Schunk DPG 100-1 is used (Figure 2).
- A wide range of sensors to improve its perception capabilities while complying with safety standards, including multiple encoders, ATI Delta torque sensors, two Sick S300 safety lasers, a Pixhawk 4 IMU and multiple optical (IDS uEye GigE) and RGB-D (Realsense D435, Kinect 2.0, Azure Kinect DK) cameras mounted on different points of the robot.

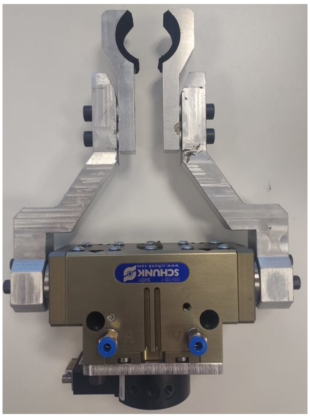


Figure 2. The pneumatic gripper used for grasping the detected objects.

2.1.1. Autonomous Navigation

One of the biggest advantages of AIMMs compared to traditional production line robots is their ability to change its workplace and to do it by its own means, navigating autonomously. This represents a great differentiating leap since there is no need to install a robot for each work cell, and a single robot can perform different tasks since its perception system allows it to adapt to each of them.

Two different levels of navigation were considered: the first one is a more general autonomous navigation in which the robot must navigate between targets, where low accuracy is required. This is typically required when moving along the workshop between workstations (global autonomous navigation). The second level is accurate autonomous navigation, in which the robot navigates in order to place itself very accurately against a target. This happens when the robot arrives to its workstation and needs to accurately place itself in the cell to successfully carry out its tasks (accurate docking).

Global Autonomous Navigation

The global navigation approach is the robot's ability to navigate between different work cells taking into account its environment. This type of navigation normally covers long distances and the accuracy requirements are in the range of several cm. The main objective is to safely and efficiently traverse the space between two approximate points.

Since 2D laser-based navigation is a well-established and proven technology [19], the approach followed has been to use out of the box components of the ROS navigation stack correctly parameterized for the kinematic characteristics of the AIMM. These components have been combined and augmented with 3D information from additional sensors to overcome some limitations of 2D navigation. Following the traditional approach, in a first learning phase Simultaneous Localization And Mapping (SLAM) [20,21] is used to generate a 2D occupancy map. The implementation used is the SLAM approach from [22], available in ROS as the package *hector_mapping*.

In the second phase, the previously recorded map is used to locate and generate traversable paths. Localization is based on Augmented Monte Carlo localization (AMCL) from [23], available as the popular *AMCL* ROS package [24].

Path planning is divided into global and local planning. Global planning geometrically computes a route between the robot's origin point and the destination point. In this proposal, the Dijkstra algorithm [25] is used, which is implemented in the ROS *global_planner* [26] package.

Local planning is responsible for computing the speed commands required to follow the route estimated by the global planner. It also modifies the original path to avoid collisions in case obstacles not present during global planning are detected. The ROS package used is *teb_local_planner* [27], which implements the Timed Elastic Band (TEB) approach [28].

Finally, the 2D navigation system was enhanced with the use of 3D information sources. The Intel RealSense D435 3D camera installed on the robot's torso provides a forward overview of the environment, detecting 3D obstacles that are projected into the costmap used for navigation.

A more detailed description of these systems and their implementation can be found in the previously mentioned report [15].

Accurate Docking

After the global autonomous navigation has driven the robot to the proximity of the operation zone, it is necessary to perform an accurate positioning to ensure a correct final placement. This accurate final placement is required to guarantee that the pieces to be detected fall within the field of view of the detecting camera.

To that end, a visual servoing-based docking system has been developed using Fiducial markers. The system is based on a proportional control that maintains and ensures, within a desired tolerance, the position of the robot with respect to the marker. A high-performance IDS Ueye camera with a sampling rate of 20 Hz is used to capture the images, allowing high control rates. Since the transformation between the camera and the robot's body is rigid, it is not necessary to perform an accurate calibration of the camera's position. Instead of directly using the estimated error in the image, the detected marker position is transformed to the robot's frame and compared with a previously recorded one from a calibrated position. This allows the camera to be mounted on any part of the robot, and in any orientation, without requiring accurate camera calibrations or modifications on how the speed commands are computed in the control program. The system is parameterizable to achieve specific speeds and accuracy. In Figure 3, the AIMM making a precise approach to the charging station can be seen.

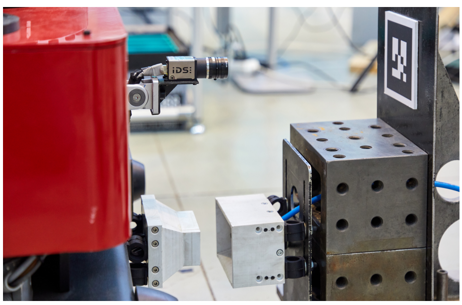


Figure 3. AIMM performing the accurate docking by detecting the Fiducial marker with the camera.

2.2. Perception System

In mobile manipulation applications, 3D object localization is very important because the relative position of the objects to work on is subject to uncertainty. Thus, the ability to recognize the object's 6D pose (i.e., to estimate object's 3D position and 3D orientation) is essential in order to grab such objects successfully.

Very common approaches are the methods based on the processing of RGB images to estimate the 6D pose of the objects. Most classical methods rely on detecting and matching keypoints with known object models [29–32]. While those approaches have good results, they generally deal badly with texture-less objects, so it still remains a challenging problem. More recent approaches apply deep learning techniques for 6D pose estimation [33–35].

Recently, methods that use 3D point clouds from RGB-D images have been introduced [36,37]. While RGB-D methods are still not comparable in performance to RGB methods for pose estimation [38–41], those methods combine visual and geometrical features, making 3D predictions more accurate. Therefore, RGB-D methods fit better for our application because they obtain more accurate predictions for 6D pose estimation than RGB methods.

2.2.1. Used Method

Our system uses PVN3D [40] to estimate the pose with 6DoF. Figure 4 shows the overall architecture of the perception module which is composed of the PVN3D architecture and a synthetic dataset. The PVN3D works on two types of features. From the RGB images, it extracts appearance information using a Convolutional Neural Network (CNN) composed of a PSPNet [42] with ResNet34 [43] pre-trained on ImageNet [44]. From the depth images, it uses a PointNet++ [45] to extract geometric features. Both appearance and geometric features are fused by a DenseFusion block [39] and are passed to a three parallel modules block composed of a 3D keypoint detection module (m_k), a per-point semantic segmentation module (m_s) and a center offset voting module (m_c). Those three modules are composed of shared Multi-Layer Perceptrons (MLPs). With the resulting semantic segmentation and center voting modules, a clustering algorithm [46] distinguishes different instances and for each instance point it votes for their target keypoints. Finally, a least-squared fitting algorithm [47] is applied to obtain the 6D pose of each instance, in the form of the rotation R and translation t that transforms from the object coordinate system to the camera coordinate system. These are obtained by minimizing the loss from Equation (1).

$$L_{\text{least-squares}} = \sum_{j=1}^{M} ||kp_j - (Rkp_j^{'} + t)||^2 \tag{1}$$

where M is the number of selected keypoints, kp_j are the detected keypoints in the camera coordinate system and $kp_j^{'}$ are their corresponding keypoints in the object coordinate system.

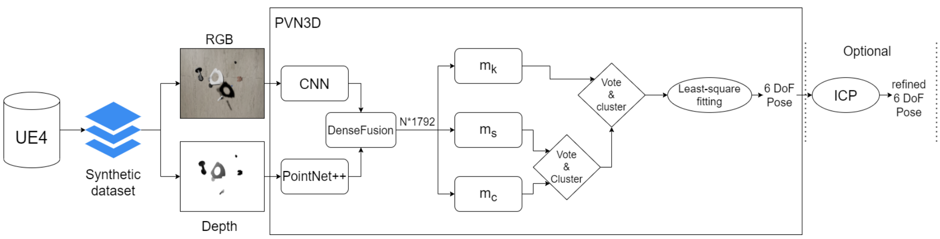


Figure 4. Perception module architecture.

2.2.2. Synthetic Dataset

A new training dataset has been created using synthetic images from the CAD models of the actual application's parts to be manipulated. As stated before, the PVN3D system has been trained using this synthetic dataset. Labeling 3D data is arduous and usually in industrial contexts it may be impossible to generate big datasets, or at the least very difficult, from real data. That is why, in many applications [48–51], synthetic data have been used recently with more frequency.

In our case, we use Unreal Engine 4 (UE4) to create the synthetic dataset. The Nvidia Deep learning Dataset Synthesizer (NDDS) [52] is a plugin of UE4 that enables to create high-quality synthetic images for deep learning applications.

The scene created is set up with a directional light, an atmospheric fog, a background plane, a distractor group, the training object group, an scene capturer and a scene manager:

- The directional light has 3.1415 lux of intensity and goes towards the background plane.
- The atmospheric fog makes the scene more realistic by smoothing far objects.
- The distractor group is composed of different geometrical shapes that are randomly generated and located over a greater area than the field of view (FoV) of the camera. That way, not every image shows all the distractors. These distractors help the deep learning methods to avoid overfitting. The number of distractors generated every 3 s is between 40 and 60.
- The background plane is randomly colored or given a texture. The color is picked from a palette of colors and the textures are random images from our laboratory's floor or workspace.
- The training group is a set of 6 objects to be detected. All of the objects are common industrial parts used in some of our projects. The spawn area is within the FoV of the camera. Thus, on every image all of the objects are present.
- The scene capturer is a virtual camera with a focal length of (320, 320) px, a principal point of (320, 240) px and a resolution of (640 $\times$ 480) px. This camera is in charge of capturing the features, including object data, color, depth, instance segmentation and class segmentation. The camera makes ten thousand captures.
- The scene manager is an optional component dedicated to control the segmentation options.

From each scene, a single RGB-D image is extracted and the scene is modified by randomly changing the 6D poses of the objects. The dataset is composed of ten thousand RGB-D images, with their corresponding semantic segmentation and instance segmentation images, and information of the objects on each image like 6D poses (locations + rotations), 3D bounding boxes and projected 2D bounding boxes.

Real cameras are not able to capture the reality with exact accuracy (i.e., they always present some kind of noise). Synthetic datasets do not present this variability unless it is specifically introduced to make the synthetic images more similar to real ones. Thus, some filters are applied to the synthetic images to that effect, both to RGB and depth images:

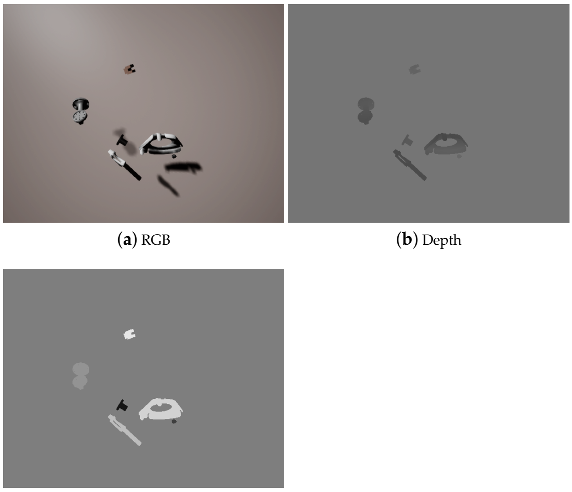
- The RGB images during training are filtered with the *rgbnoise*. This filter is applied only once with a probability of 0.8 and twice with a probability of 0.2. The filter is composed of an HSV augmentation, a linear motion blur with a probability of 0.2 and a Gaussian filter with a probability of 0.2. The Gaussian filter is applied with a window of 3 $\times$ 3 for 80% of the cases and with a window of 5 $\times$ 5, otherwise.
- The depth images are filtered during training with a Gaussian filter with a window of 3 $\times$ 3 in the depth component, keeping the spatial distribution.

Figure 5 shows the 6 real objects to be detected. All of them are industrial parts that have been used in our projects.

(**a**) Object 1 (**b**) Object 2 (**c**) Object 3 (**d**) Object 4 (**e**) Object 5 (**f**) Object 6

Figure 5. Set of six industrial objects selected to appear in our dataset.

Figure 6 shows an example of RGB, depth and semantic segmentation images obtained from the UE4. RGB and semantic segmentation images are 8-bit images. Depth image is a 16-bit image measured in cm.



(a) RGB (b) Depth

(c) Semantic segmentation

Figure 6. Output images from the UE4. Depth image has been adapted for visualization.

2.3. Calibration Process

An accurate manipulation system requires that all of the components that will intervene in the detection and manipulation processes are accurately calibrated. To calibrate the vision system, it is necessary to obtain the intrinsic and extrinsic parameters of the camera. The intrinsic parameters are the representation of the optical center and focal length of the camera, while the extrinsic parameters represent the camera's position relative to the world, in this case relative to the robot.

To calculate the transformation ${}^{flange}H_{camera}$ between the robot flange and the camera, which has been mounted in an eye-in-hand configuration, an automated hand-eye calibration procedure has been used. Based on an initial approximate camera pose ${}^{flange}H'_{camera}$ provided by the user and an initial calibration pattern detection ${}^{camera}H_{calpattern}$, an approximate pose of the calibration pattern is estimated as

$$ {}^{base}H'_{calpattern} = {}^{base}H_{flange} * {}^{flange}H'_{camera} * {}^{camera}H_{calpattern} \tag{2} $$

This approximate calibration pattern pose ${}^{base}H'_{calpattern}$ is used to calculate a set of robot poses ${}^{base}H^{i}_{flange}$ that will be used to move the robot and obtain new images where the calibration pattern can be found. Specifically, the poses are calculated as

$$ {}^{base}H^{i}_{flange} = {}^{base}H'_{calpattern} * {}^{calpattern}H^{i}_{camera} * {}^{flange}H'^{-1}_{camera}\,,\ i = [1...n] \tag{3} $$

where the approximate calibration pose ${}^{base}H'_{calpattern}$ and camera pose ${}^{flange}H'^{-1}_{camera}$ are provided in the previous steps and the relative poses between calibration pattern and camera ${}^{calpattern}H^{i}_{camera}$ are generated automatically, adding some small random translations and rotation.

Based on these poses, the robot is automatically moved to acquire images and estimate the calibration pattern pose in each of these images. This procedure will generate a dataset of N pairs of robot and calibration pattern poses.

$$data_i = ({}^{base}H^i_{flange}, {}^{camera}H^i_{calpattern}). \quad (4)$$

These data are used to estimate the final camera pose ${}^{flange}H^*_{camera}$ using Ceres Solver [53] to perform a non-linear optimization where the cost function is calculated as:

$$cost_i = ({}^{base}H^i_{flange} * {}^{flange}H^*_{camera} * {}^{camera}H^i_{calpattern})^{-1} * {}^{base}H^*_{calpattern} \quad (5)$$

where the camera pose ${}^{flange}H^*_{camera}$ and calibration pattern pose ${}^{base}H^*_{calpattern}$ are optimized during the process.

In addition, the calibration of the gripper installed in the flange of the robot is also necessary. The center of the two fingers has been calibrated as the tool center point (TCP) by means of the *three point method* provided by the robot manufacturer.

With these calibration processes, the entire system consisting of the arm, camera and tool (end-effector) has been referenced in a common frame.

2.4. Process Control and Programming

2.4.1. Skill-Based Programming

Industrial tasks are usually composed of a sequence of operations, each dependent on the previous one. Thus, the AIMM has to be able to perform this ordered sequence while managing and controlling the execution flow and any possible errors. Following the advances presented in [54], where the concept of "skill" is presented as a nominative entity of a capacity learned by the robot, which, due to its similarity with human behaviors, make its understanding and handling easier.

In this work, the concept of skill is used to represent each capacity that the robot has acquired. Thus, it is easier to identify what skills are needed to perform a given task. For the use case presented in this paper, the most relevant skills are the following:

- Navigation: composed by the techniques presented in Section 2.1.1: Global Autonomous Navigation;
- Docking: wraps the capacity shown in Section 2.1.1: Accurate Docking;
- Object pose estimation: allows using the techniques presented in Section 2.2;
- Object grasping: successive robot movements that align the robotic arm to the detected object to, then, actuate a gripper that allows grasping an object;
- Undocking: using the same concept of docking but in the inverse way (where less accuracy is required).

To represent the execution flow, the concept of state machines is used. These machines manage the skills used to perform a certain task. This state machine approach facilitates programming for non-expert operators, making it possible to do modifications to the robot's tasks in a simple and visual way, including management of possible errors. In the following sub-section, more details about the implemented approach can be found.

2.4.2. Skills Management by State Machine

Once all the robot skills necessary for the correct execution of the task have been defined, it is necessary to manage them. Each skill has an internal flow of atomic operations that provide an output. Moreover, a skill can suffer errors or not be able to perform its function correctly. To manage all possible cases, it is necessary to use a higher level tool, in a higher layer of abstraction. In this work, the use of state machines allows managing and orchestrating the developed skills required for each task. After testing different state machine libraries like [55] and custom developments, following works such as [56], it was decided to use Flexbe [57] as a manager.

Flexbe is a behavior engine that allows the generation of state machines to encode behaviors in robotic and automation applications. As can be seen in Figure 7, the skills can be sequenced in a state machine that manages the required behavior, linking the output and inputs of the skills and handling the errors that eventually can occur.

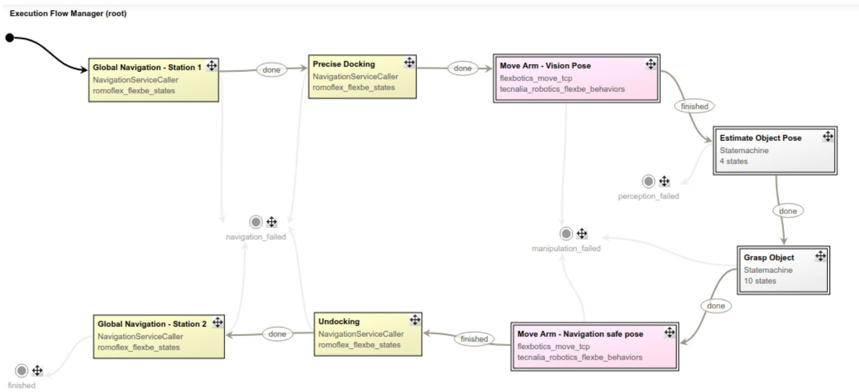


Figure 7. Developed skills sequenced in a Flexbe behavior.

The required functionalities to carry out these tasks have been encoded in a modular way organized in different ROS packages that offer an interface (common communication mechanisms in ROS, such as services [58] or actions [59]) that allow them to be invoked by the task manager. These blocks can be made up of different sub-blocks, conforming the previously mentioned skills (Section 2.4.1). This block can also have different outputs depending on the result. In the performed experiment, the object estimation skill is composed by a set of required operations that complement the pure vision operation (see Figure 8). First of all, the mobile elements must be stabilized and, after the perception result is obtained, it must be transformed to the robot base coordinate frame for further use.

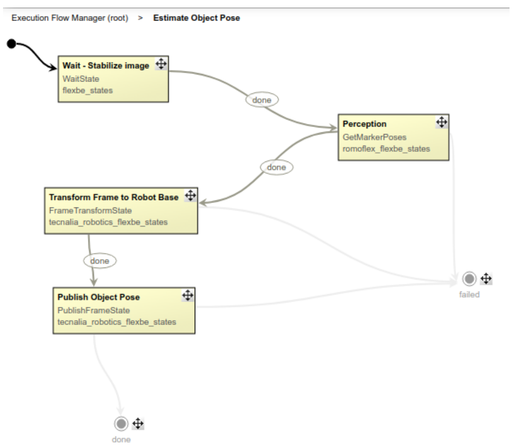


Figure 8. Estimate object pose skill is composed of additional operations that complement vision algorithms.

Regarding the grasp skill, taking as input the object estimated position computes the required approach, pre-grasp and retreat poses. The grasp skill sequences the calculated waypoints and interacts with the gripper for grasping the object when the robot arm is precisely aligned to it. Figure 9 illustrates all the involved states in the grasp operation.

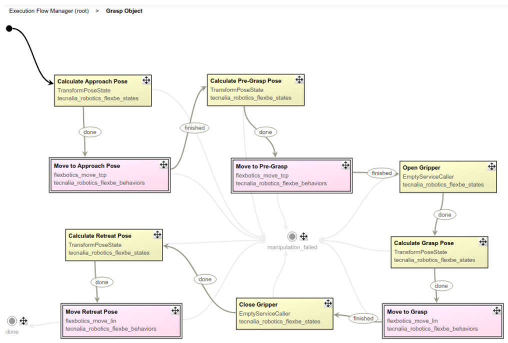


Figure 9. Grasp skill is composed of sequential robot movements and gripper operations.

The complete operation has been shown in Figure 7. There, the estimation and grasp skills are complemented with navigation and docking skills to complete the full operation.

3. Experiment Definition

The experiment consists of the correct execution of a paradigmatic operation for an AIMM in modern industry: to go to some workspace and manipulate a part. This operation is composed of a series of tasks which include autonomous navigation, artificial perception, manipulation and grasping and global management of the application execution flow.

The starting point is established in the electrical charging spot of the robot. A new task order is received in which the point goals where the robot has to navigate autonomously are established. By processing the data from its sensors, the robot is able to correctly locate itself in the environment and navigate towards the established objective. As mentioned in Section 2.1.1: Global Autonomous Navigation, the technology used, based on SLAM by a 2D laser, has an intrinsic error that can reach several centimeters of deviation in the location. Thus, a final precise navigation process is required once in the proximity of the goal to achieve a predefined and known required accuracy. This accurate position will ensure that the part falls both in the camera's field of view and the space reachable for grasping.

The robotic arm moves to a known position to focus the camera on the target object area. The camera used is an Azure Kinect DK by Microsoft. This camera is a developer kit that contains a best-in-class 1MP depth camera, 360º microphone array, 12MP RGB camera and orientation sensor. The RGB and depth images are obtained with the Azure Kinect DK and passed to the perception module. First, the point cloud is obtained from the depth image. That point cloud is filtered to clean noise, background data and the floor. The cleaned data with the RGB image are passed through the trained PVN3D model and the 6Dof Pose is predicted. The predicted pose is then refined with ICP to improve the results.

After detecting the desired object and obtaining its relative position in space, the grasping task is launched. In normal operation, this task would be composed of an approach maneuver by the robotic arm plus grabbing the object by means of the pneumatic gripper. However, developing or implementing an accurate grasping strategy is outside the scope of this paper. Thus, we will consider the grasping task successful if the gripper is able to touch the centroid of the object, in the assumption that, if given that reference point, a proper grasping method would be able to grab it correctly.

If there is no error and the object is correctly grasped, the arm is retracted to a safe navigation position that prevents it from colliding with obstacles. Then the AIMM navigates autonomously to the position where an operator will receive the requested object, completing the operation.

Possible errors in the application are managed through specific states of the Flexbe state machine. These states control the possible errors of the task execution process and take actions accordingly in each case.

4. Results

The results obtained can be measured by the success of both the whole operation and of each of the individual tasks it is composed of.

The results of the navigation and accurate docking part have been successful. In forty tests of navigation and accurate docking done in the real test environment, the operation was successful 100% of the times from different starting positions and with target positions in different orientation configurations.

To evaluate the maximum tolerances of the accurate docking, a battery of tests has been performed setting multiple starting locations with attack angles with respect to the docking station ranging in $\pm 50^{\circ}$, at different distances. In this setup, the system was able to successfully dock from almost any distance, failing only at extreme angles (>45º) at very close distances (<60 cm), where even small movements can take the marker away from the camera's field of view. In all other cases, the robot is capable of carrying out the accurate docking process without any problem.

The perception module has been trained with the synthetic dataset, using a proportion of 0.85 for training and 0.15 for testing. The metric used to test the perception module is ADD(S) [36,38,39], as the authors of PVN3D [40] evaluated it. The results are shown in Table 1.

Overall, location and semantic segmentation are done correctly for all the objects, but rotation is not correctly obtained for some of them. Furthermore, if we compare the three losses of the three submodules of the perception module (Table 1), we can see that the semantic segmentation module and center offset module losses are of, at least, an order of magnitude less than the keypoint detection module ones. This is why, in many of our experiments, location and segmentation of the objects are predicted correctly but rotation is not that accurate. The symmetric objects are better detected than the not symmetric ones because there are more possible rotation solutions on symmetric objects. Even if rotation is not really accurate, this can sometimes be fixed by applying an ICP to the obtained pose. This refinement only improves the obtained pose if the initial pose is similar enough to the ground truth. All the detection phases are shown in Figure 10.

Table 1. Losses and evaluation of perception submodules on ADD(S) obtained in the test. Symmetric objects are in bold.

	$L_{keypoints}$	$L_{semantic}$	L_{center}	$L_{multi-task}$	**ADD(S)**
Object 1	0.9738	0.0275	0.0427	1.0715	5.12
Object 2	1.8951	0.0278	0.0538	2.0045	1.02
Object 3	0.4216	0.0068	0.0223	0.4574	86.05
Object 4	0.9789	0.0146	0.0451	1.0533	8.77
Object 5	0.1795	0.0077	0.0076	0.2025	68.89
Object 6	0.4247	0.0092	0.0157	0.4587	87.47

As can be seen in Figure 11, the tests carried out with real data have obtained a similar behavior. For almost all of the objects the position is predicted correctly, but the rotation incorrectly. Object 4 is incorrectly located in almost all the testing images. The possible cause could be that its metallic surface has many reflections that create lots of noise in the camera.

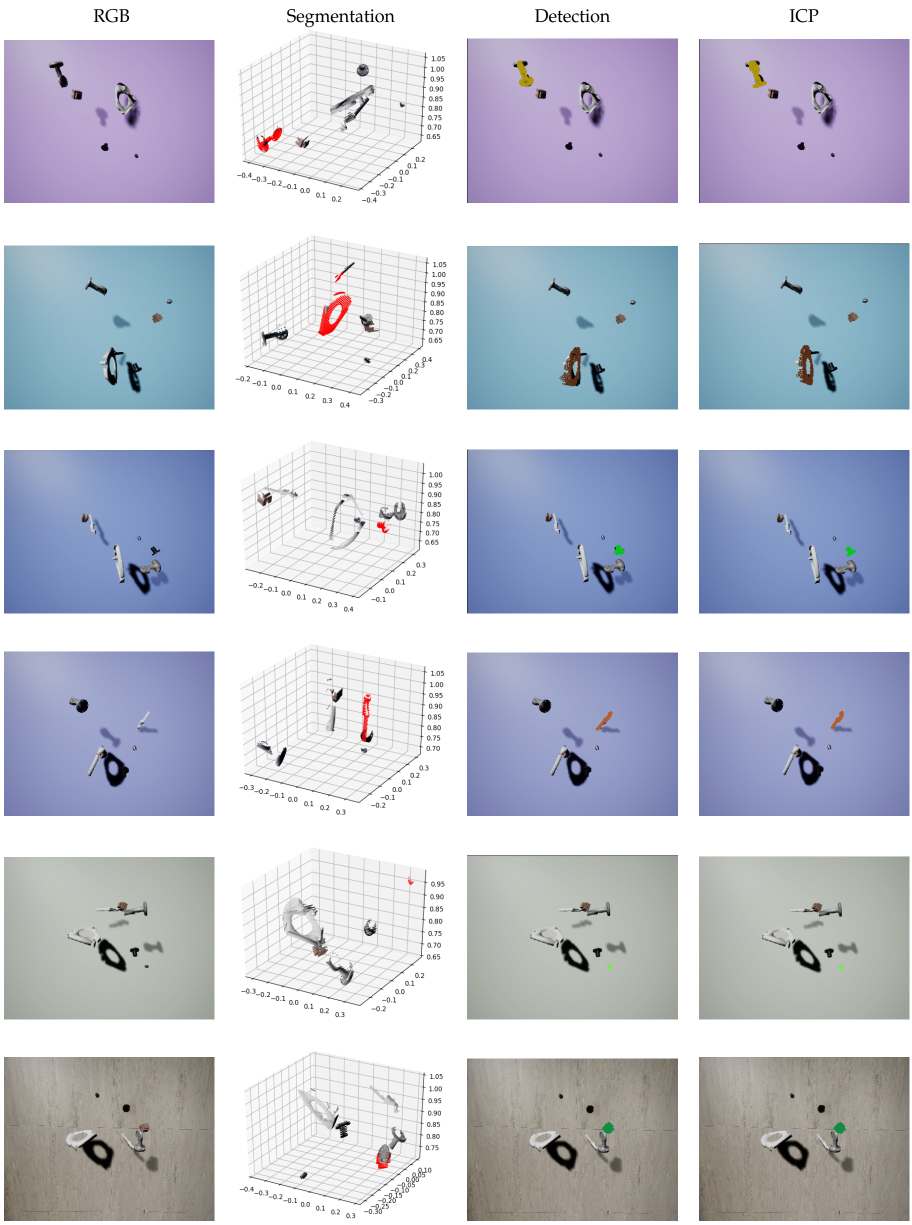


Figure 10. Detection results of the synthetic data. Each row corresponds to an object from Object 1 to Object 6.

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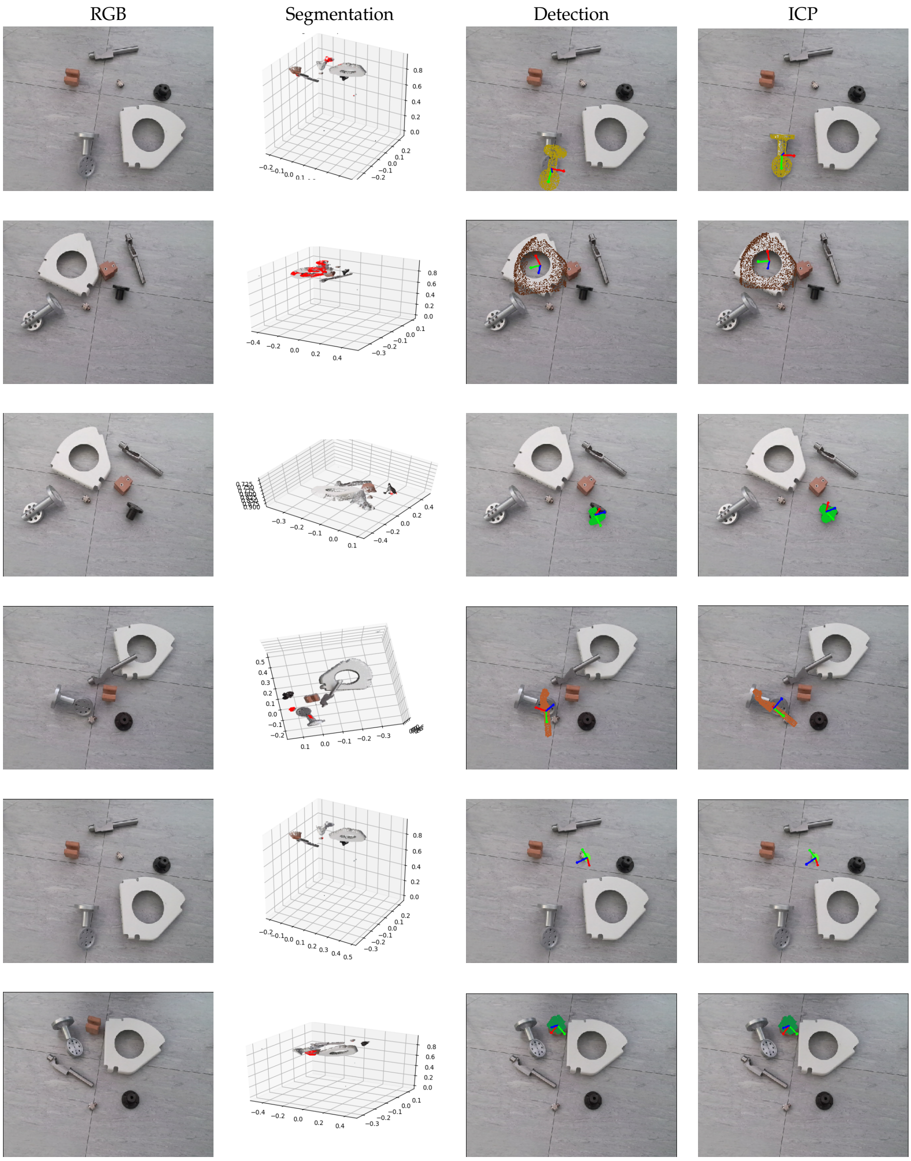

Figure 11. Detection results of the real objects. Each row corresponds to an object numbered from Object 1 to Object 6.

The camera–robot calibration process explained in Section 2.3 returns a calibration transformation given a set of images. For each image, the ${}^{base}H_{calpattern}$ transformation can be calculated using the optimized transformation. In a perfect calibration, all the resulting poses should be equal although it is hardly possible as the process includes errors such as intrinsic robot calibration errors and camera calibration errors. Therefore, the mean ${}^{base}H_{calpattern}$ transformation error (i.e., the average error in the estimation of the calibration pattern's position) in this setup is 0.00166856 m in translation and 0.00386598 rad in rotation. Based on our experience calibrating other robotic systems, these values are considered accurate enough to correctly perform the proposed grasping task based on the used hardware.

The overall operation has been done thirty times. The obtained results are shown in Table 2. The first column named "# executions" indicates the number of times the overall application has been performed. The second column "# successful executions" shows how many times the application has been executed successfully (that is, the AIMM has navigated autonomously to the target goal, performed the docking process accurately and finally detected and touched the centroid of the object). The achieved success rate is directly co-related with the output of the perception module. For instance, Object 4 is the object that obtains the worst results because the perception module predicts its pose incorrectly.

Table 2. Overall operation results.

	# Executions	# Successful Executions	%
Object 1	7	6	85.71
Object 2	4	3	75
Object 3	5	5	100
Object 4	3	0	0
Object 5	6	6	100
Object 6	5	5	100
Total	30	25	83.33

5. Discussion

The main bottleneck in our application is the perception module. The problems reported in the estimation of the orientation part of the objects' 6D pose make the grasping operation difficult. Thus, the perception module must be improved before trying to introduce any grasping strategy in the system. The keypoints detection module is the most complex task to be carried out within the perception system. This is because the system needs to learn specific points of the objects in the scene. Thus, a dataset very rich in variability is critical to successfully train it. While the current dataset's variability seems enough for the other training tasks, it is possible that it is still lacking for training the keypoints. Further effort should be put into improving the dataset's variability.

One possible source of the problems detected in the perception module probably comes from the synthetic dataset. Due the complex nature of the RGB-D systems, the synthetic dataset may not be realistic enough to simulate a real one, especially regarding the noise in the depth information. While the introduction of synthetic noise in RGB is a well studied problem and can produce realistic results, the noise introduced in the depth information by reflections or different colors is a very complex problem for which no proper model exists yet to the knowledge of the authors. Thus, the dataset does not store properly the variability introduced by this type of noise. A way of introducing more realistic noise in the depth component should be studied further.

Another way of improving the dataset by increasing its variability would be to introduce more objects to help the model to learn more generic features. In addition, according to [60], combining domain randomization datasets, which is the type of dataset we generate, with photorealistic images increases the performance of models on synthetic datasets. All mentioned aspects considered, future works could include adding synthetic photorealistic datasets generated with Blender.

The developments presented in this paper have been carried out in a provisional AIMM while the robot for the execution of the use case of the European Sherlock project was being manufactured. After the validation of the real tests, current developments will be migrated and deployed in the new robot (Figure 12).

Figure 12. New AIMM of the European Sherlock project that was designed and manufactured during the testing and writing of this paper.

6. Conclusions

In this article, we presented a solution to a paradigmatic, usual task that AIMMs in industrial environments should be able to carry out, composed of navigation, perception and manipulation of objects.

To carry out this task, an AIMM equipped with the most modern sensors is used. Those sensors provide the robot with the capacity to perceive the environment in a wide range of forms (2D LiDAR, RGB, 3D), enabling it to achieve a high level of autonomy. A calibration process ensures that both the equipped sensors and the gripper used in the robot are accurately referenced.

Combining global navigation and accurate docking technologies, the robot is capable of autonomously navigating between different locations in the workspace and reaches targets accurately with defined tolerances. To detect the objects to manipulate, a deep-learning perception system based on 3D vision is used. Using the images obtained by the camera and a depth learning system, the robot is able to estimate the position of the object after having previously trained with synthetic data that represent real objects. The perception method is able to estimate the object's pose with high success rate, while having problems to estimate the orientation.

For the process' work flow management, a skill-based state machine system is used. Each operation to be carried out is decomposed in a sequence of smaller, atomic tasks that try to be recognizable and easily assimilable for human operators. These task or skills can be combined to create different sequences for different operations. The skill work flow for the operation is introduced in a state machine, where all the skills necessary to execute the task are ordered, monitored and managed.

The complete system presented, implemented in the AIMM, has been able to perform the proposed paradigmatic industrial operation in a real environment with an average 83.33% success rate.

The main contributions of this article are summarized in the correct achievement of a real industrial application through the use of an advanced robot and in the integration of different available techniques and methods in one system. Additionally, a new RGB-D training dataset that uses synthetic images of real industrial parts has been compiled and will be made available.

Further lines of work will include changing the synthetic dataset generation by adding photorealistic images with blender in order to improve the vision system, include a grasping module to manipulate the detected objects and migrate all the developed modules to the new robot. Within the framework of autonomous navigation, it has been proposed to add 3D information through the inclusion of new sensors (Lidar 3D, RGBD/stereo camera) to increase the perception of the robot and make it capable of navigating more robustly and safely using SLAM3D techniques.

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Abbreviations

The following abbreviations are used in this manuscript:

AIMM	Autonomous Industrial Mobile Manipulator
AMCL	Augmented Monte Carlo localization
CNN	Convolutional Neural Network
CPPS	Cyber-physical production systems
HRC	Human Robot Collaboration
HSV	Hue, Saturation, Value
MLPs	Multi-Layer Perceptrons
NDDS	Nvidia Deep learning Dataset Synthesizer
RGB	Red, Green, Blue
RGB-D	Red, Green, Blue, Depth
ROS	Robot Operating System
SLAM	Simultaneous Localization And Mapping
TEB	Timed Elastic Band
TCP	Tool Center Point
UE4	Unreal Engine 4

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9 Robotic solution for opening doors in contained or high biological risk facilities

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ROBOTIC SOLUTION FOR OPENING DOORS IN CONTAINED OR HIGH BIOLOGICAL RISK FACILITIES

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ABSTRACT:

In a context of a pandemic caused by the SARS-CoV-2 virus, there is a need to disinfect busy areas such as schools, hospitals, nursing homes, laboratories, public transport, etc. using techniques that pose a risk to health. In turn, the robotics industry is at a pivotal moment with great developments and applications in numerous applications. Therefore, the figure of robots is of great interest as they have the ability to perform these tasks autonomously. However, there are great challenges in current robotics that must be resolved in order to perform tasks correctly. This is the specific case of door opening. Something necessary since to achieve a complete disinfection the robot must go through all the rooms of the installation.

In this work, a solution to the problem of opening doors is presented by means of a mobile robot to which artificial perception techniques are applied for detection, handling and autonomous navigation.

Keywords*: autonomous navigation, artificial perception, learning by demonstration, skills-based programming, door opening, AIMM, mobile robotics, sensor fusion*

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Applied to the BOTA-ROBOTA project. *Robot for Covid-19 disinfection purposes capable of opening doors to move around inside buildings autonomously.*

1.- INTRODUCTION

When talking about robotics in general terms, the first ideas are associated with large electromechanical devices providing solutions to industrial manufacturing, automation and logistics processes. These automatons, which perform repetitive, costly and low value-added tasks, have been at the heart of the expansion of robotics during the 20th century. Today, robots are equipped with a multitude of sensors that give them a better perception of their environment and, therefore, greater autonomy and versatility. Thanks to these new capabilities and technological advances, robots are much closer to humans in both industry and everyday life.

This paradigm shift in modern robotics has led to the growth of the sector beyond the industrial realm [1], generating a great interest in companies, which are increasingly investing in multiple sectors [2]. A paradigmatic example arising from these new capabilities are the mobile industrial manipulators or AIMMs [3], in which a mobile base is combined with one or several industrial manipulators and a wide range of multimodal perception sensors.

Thanks to these capabilities, robots are no longer considered a static production element and their use has spread to a multitude of applications in various fields. For example, social and service robotics is undergoing a large-scale technological revolution. According to the annual *WorldRobotics* survey of the International Federation of Robotics (IFR) [4], the application of machine learning, artificial intelligence, adaptive computing and machine vision have greatly enhanced the capabilities of robots, driving growth in a sector where sales of professional service robots increased by 41% and consumer service robots by 16% in 2020.

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The Covid19 pandemic has also spurred this expansion [5], as many companies have embraced digitization and automation, employing robots to improve efficiency and optimize their processes, while generating a new focus on how the capabilities that robots have been developing can be applied to this area. Fig.1 in the appendix shows the segments of service robotics that are growing the most due to the additional demand produced by the pandemic.

This is the context of the Bota-Robota project, subsidized by the "Euskampus Resilience COVID 19" program [6], whose objective is to support and catalyze collaborative projects oriented to challenges related to COVID19 and that have a high potential for social impact.

Within the framework of this research project, this work presents a possible robotic application that provides a solution to a problem inherent to a pandemic situation such as that produced by the SARS Cov2 virus, such as the risk of exposure of health or auxiliary personnel in certain situations.

In this paper we show how the tools and skills that have been developed for AIMMs in other contexts, especially industrial ones, are also applicable in this healthcare context. Specifically, we address a problem inherent to indoor spaces where the need arises for the robot to be able to access different locations by opening doors in contained or high-risk facilities.

2.- MATERIALS AND METHODS

2.1.- INFRASTRUCTURE

The proposed challenge requires both object manipulation and autonomous navigation capabilities. Therefore, the robot used has been a novel AIMM that has been co-designed by the author within the framework of the European SHERLOCK project. Thanks to its technical characteristics, this robot is able to perceive its environment due to the artificial perception sensors that have been selected and conditioned for the robot. Furthermore, it can navigate autonomously and safely as it detects and dodges possible obstacles and takes into account changes in its environment. Additionally, the robot is able to perform manipulation tasks with its two arms and the grippers that have been designed and manufactured by the author for this purpose (Fig. 1). Additional information on the robot can be found in section 1.2 of the appendix.

Fig. 1. Robot (AIMM) used in the tests, together with the gripper used for door opening.

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2.2.- TECHNOLOGIES

2.2.1.- Autonomous navigation and accurate positioning

The main advantage of AIMMs over conventional manipulators is their ability to work in different locations, as they are able to navigate autonomously in their environment.

Two different levels of navigation have been considered in this application: the first one is a more general autonomous navigation in which the robot navigates between targets, where little accuracy is required. This is usually necessary when moving along different rooms (global autonomous navigation). The second level, the robot is positioned very accurately against a target. This happens when the robot arrives at the door it wishes to open and needs to position itself accurately with respect to it in order to perform the task of sensing and manipulating the handle successfully (accurate navigation).

2.2.1.1.- Global autonomous navigation

Global navigation is considered to be the robot's ability to move efficiently and safely, reaching its destination taking into account the changes and possible collisions that may occur along the journey, adapting its trajectory accordingly.

The implemented navigation is based on environment perception techniques by means of 2D laser technology and SLAM, a well-studied and proven technique [7]. For this application, the navigation suite available in ROS has been used, performing a fine tuning process of the parameters of the navigation packages provided for the specific dynamics and kinematics of the robot and the constraints imposed by the problem of traversing doors, with lateral tolerances of a few centimeters.

More information about the techniques and algorithms used can be found in section 1.3.1 of the annex.

2.2.1.2.- Accurate navigation

Once global navigation is completed, the robot will be in the vicinity of the target with a positioning error of ±5cm on average, to which the angular error that has occurred must also be added. Accurate positioning is therefore necessary to ensure that the door handle enters within the limited field of view of the robot's integrated perception system.

For this purpose, a docking system developed by authors [8] based on the detection of fiducial markers have been used. The system consists of a proportional control that maintains and ensures, within a desired tolerance, the position of the robot with respect to the marker. An IDS uEye [9] high resolution camera with a sampling rate of 20 Hz is used to capture the images, which allows high control rates and reduces the error per pixel. The position error between the two is translated, within a closed loop, into a velocity setpoint that is sent directly to the robot drive system, a control process known as *Visual Servoing*.

2.2.2.- Door perception and detection

Door detection has been carried out by using an iterative method called RANSAC [10], which is able to estimate the parameters of a mathematical model from a set of data in which there may also be values not belonging to that model. Thanks to the point cloud provided by the robot's sensors, the plane with the greatest support has been detected, that is, the one with the greatest number of points that meet the condition of being at a set distance from the model of the lower plane. In this way, it is possible to correct both the noise in the data and the small inaccuracies in the alignment of the detected plane with the real position of the door. All the developments in this section have been carried out in the Python programming language using the Open3D library [11].

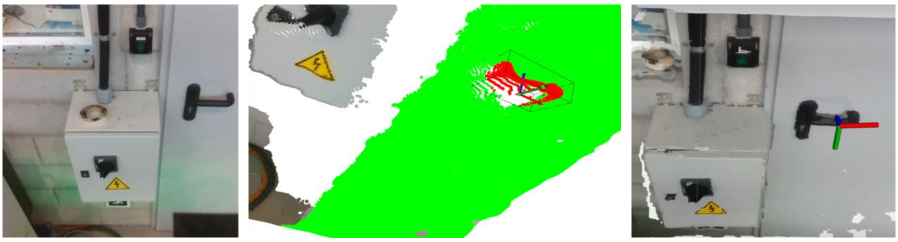
To avoid confusion with the wall, since it is possible that the plane corresponding to the wall may be erroneously detected as a door, the space between the detected plane and the robot is segmented and it is observed if there is a cluster with the approximate expected dimensions of the handle near that plane. If there is no such cluster, it is inferred that the detected plane corresponds to a wall, whereas, if more clusters are observed or of different size than expected by the handle, it is assumed that it is an area of the scene not corresponding to the door.

Once the door and the approximate cluster where the handle is located have been detected, it is necessary to estimate its position and orientation in order to provide it to the robot so that it can perform the corresponding manipulation task. For this purpose, the cluster is refined by filtering its elements through the color difference with respect to the predominant color of the door. This step is based on the precondition that the color of the handle is different from the color of the door. If this is not the case it is still possible to detect the position of the handle with sufficient accuracy, but this assumption increases the robustness of the process. As a final result, the robot is provided with the position of the gripper point together with its orientation in space.

Ideally, the attachment point and orientation could be obtained by calculating the minimum parallelogram encompassing the handle from its boundaries. However, due to noise in the point cloud, on multiple occasions the minimum parallelogram obtained using the Open3D-based system does not turn out to be completely parallel to the door, thus invalidating the position of the clamping point. To solve this problem, the handle points have been projected in two planes parallel to the door, both behind and in front of the door (in relation to the robot), so that the minimum parallelogram obtained, adding these points to the handle cluster, is parallel to the door. However, it is still possible that there is some error in the orientation because the angle of the handle in relation to the ground has not been accurately detected. To minimize this error, different observations are taken and an estimate is made from them.

A more detailed description of the screening process can be found in section 1.4 of the annex.

In the Fig. 2 the result of this process can be observed where, starting from a point cloud obtained by the RGBD camera installed on the robot's gripper, the system is able to estimate the position of the handle indicating its coordinates in space.



(a) *(b)* *(c)*

Fig. 2: (a) Real image of the door and the handle. (b) Area of interest obtained by segmenting the space between the plane and the robot and refining the detected cluster. *(c)* Point of attachment of the handle in space.

2.2.3.- Handle manipulation

An approach based on the *learning-by-demonstration* paradigm is used for handle manipulation [12]. This allows both expert users and those with no previous experience in robotics to teach the robot the different maneuvers to be performed during door opening. The main idea is that the user guides the robot's gripper in the different movements that make up the operation while the application collects information from the robot to be able to reproduce it in subsequent executions.

The learning-by-demonstration application consists of the following modules, an extended explanation of which can be found in section 1.5 of the annex:

- **Data acquisition:** Stores information on the robot's position.
- **Path analysis and filtering:** Filters to manage and modify paths.
- **Path execution:** Capable of executing paths stored in the database.
- **User interface:** Graphical interface designed to facilitate the use of the learning-by-demonstration tool. See Fig.5 in the annex.

For door opening, the handling task has been divided into four phases: 1) handle holding, 2) handle turning and initial opening of the door and 3) wide opening of the door and 4) final impulse. This division is due to the fact that the dimensions of the door and the arm do not allow this to be done in a single movement. In addition, this division simplifies the learning task and avoids user errors when trying to perform a complete demonstration of the whole task. The Fig. 3 shows an example of learning, in which the user guides the arm with one hand while holding a tablet with the interface in the other.

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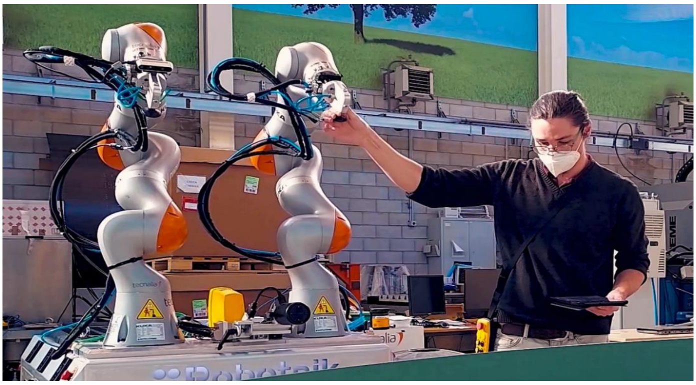

Fig. 3. Learning the trajectories for door opening application.

2.2.4.- Skills-based programming

The door opening process can be defined as a succession of tasks that the robot must perform autonomously. The programming of this process has been carried out following the advances presented in [13] where the concept of skill is presented as a nominative entity of a capacity or ability of the robot that it is able to perform autonomously.

Each skill represents a singular operation or task (object detection, tool operation, arm positioning, drilling, etc.). Encapsulated in the skill concept, each task acquires a higher level of abstraction, making it easier to manage the execution flow and achieve a more robust system in the face of changes and errors.

Skills can be combined with each other to generate new, more complex skills. In that way, specific solutions are created to solve new problems. This skill-based approach reduces the time spent on programming and allows the reuse of the learned skill in other similar processes by correctly adjusting the input and output parameters of the skill in question. Skill management is performed by means of a graphical interface developed by the authors (Fig. 4).

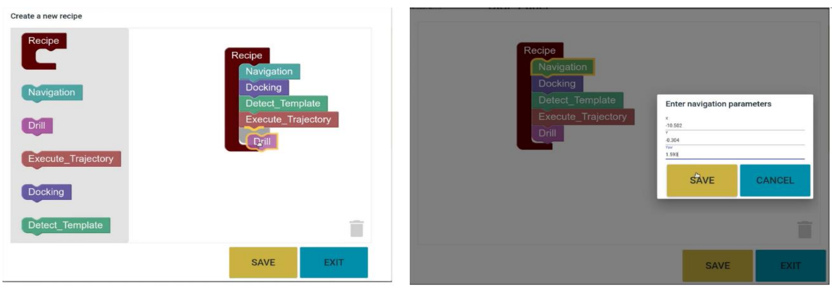

Fig. 4. Graphical interface developed for the creation and parameterization of a list of skills learned by the robot.

There is a preliminary phase in which the skills that the robot must learn to perform its task are identified. For the solution presented in this paper, the most relevant skills are the following:

- Global navigation
- Accurate navigation
- Handle perception
- Learning by demonstration
- Handle manipulation
- Door opening

The robot must be able to perform this ordered sequence while managing and controlling the execution flow and possible errors. For this purpose, a state machine skill based management system (Flexbe) is used. **[14]**.

3.- RESULTS

The results obtained have been evaluated by measuring the success rate based on the execution of each of the phases that make up the complete task, considering that the results of certain phases depend on the previous one. For this purpose, the number of times that the skill result has been correctly executed based on different configurations and input parameters has been quantified.

The test consists of the robot navigating autonomously from a random starting point to the vicinity of the target door. Once there, it must detect the marker that will serve as a reference to position itself precisely in front of the door. After that, the robot will detect the handle and obtain its position in space, which it will use as an input parameter to manipulate the handle. Once the door handle is turned, the robot will proceed to open the door by exerting the force and movement previously learned by demonstration, modifying the trajectory as necessary to adapt to the changes with respect to the learning. Once the door is fully open, the robot will proceed through the door and continue its navigation path. The Fig. 5 shows the execution flow of the completed task.

Fig. 5. Task execution flow for door opening.

Ability	Number of tests	Success rate	Notes
Autonomous navigation (gate approach)	20	20/20 - 100%	10 tests - different start same end 10 tests - different start different end
Accurate navigation	10	10/10 - 100%	If the marker is visible to the camera, the system is able to accurately approach the robot 100% of the time.
			Slight accuracy errors in the estimation of the clamping point due to measurement noise. This resulted in two occasions

Perception handle	55	53/55 - 96%	when the handle was not manipulated correctly, preventing the door from opening fully. 30 tests in simulation 25 real tests
Handle manipulation	25	23/25 - 92%	On two occasions the foam of the gripper slipped and did not open correctly, leaving the door stuck.
Door opening	30	26/30 - 86%	On 3 occasions the door bounced open with too much force. On 1 occasion it did not open wide enough.
Autonomous navigation (through door)	10	10/10 - 100%	After opening the door correctly, the robot successfully entered the next room.

Table 1. Results obtained in the performance tests

4.- CONCLUSION

In the context of a pandemic caused by the SARS-CoV-2 virus, this paper proposes a solution to the problem of opening doors in contained or biohazardous areas. This task, so common for people, is a great technological challenge for a robot as it requires perception, autonomy and dexterity.

A solution based on the combination of artificial perception techniques, autonomous navigation and automatic learning by demonstration is presented, where the programming of the tasks is done in a simple way using the concept of robot skills, enabling the reuse and adaptation of these skills by simply modifying their input and output parameters. We have worked on improving the user experience by developing web interfaces that facilitate the programming and behavior management of the robot.

By means of this combination of techniques applied in the mobile manipulator presented, it has been possible to successfully open and pass through the doors of the laboratory and workshop of Tecnalia's facilities, as can be seen in [15].

As an aspect to be reviewed in future developments, it should be noted that, due to the limited reach of the arm, there was no control of the degree of opening of the door, which could bounce or remain slightly ajar in the process. This does not pose any risk to the robot since, thanks to its perception systems, it can detect that the opening has not been complete, avoiding a possible collision since it can prevent the robot from having enough space to pass through the opening.

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SUPPLEMENTRAY MATERIAL

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1.1 TRENDS IN SERVICE ROBOTICS

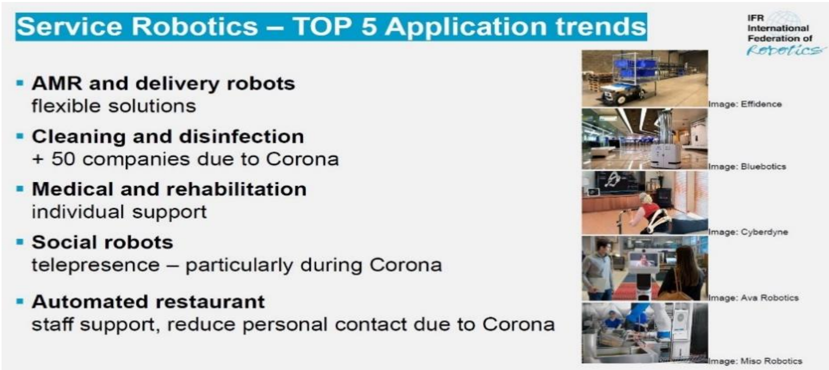

Fig. 1. IFR - Top five application trends for professional service robots were driven by additional demand from the global pandemic. © IFR International Federation of Robotics

1.2 ADDITIONAL INFORMATION ABOUT THE ROBOT

The mobile base is able to move holonomically thanks to its four mecanum wheels [1]. This enables movement in all directions of the plane, including translation and rotation, giving it essential maneuverability in confined spaces.

In terms of safety, the AIMM has a complete safety system according to ISO 3691-4:2020 that allows it to share its workspace with people. A PLC system manages the overall safety of the robot, collecting information from the different sensors (2D LIDAR, IMU, encoders, RGBD cameras, BMS system) and managing and modifying the speed and safety zones of the robot according to its environment.

The handling system consists of two KUKA IIWA collaborative manipulators [2] with 7 kg load capacity each. They have 7 degrees of freedom, which significantly aids the resolution of possible joint configurations for manipulating objects. These robotic arms come equipped with torque sensors at each joint, which are used in this work to sense the force the robot exerts when actuating the handle and swinging the door. This capability is used to ensure that the arm is holding and executing the opening maneuver correctly.Fig. 2 shows the CAD model and the kinematic chain of the KUKA IIWA robot.

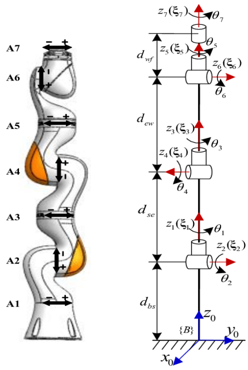

Fig. 2. Model and kinematic chain of the KUKA IIWA robot.

The gripper used for the manipulation of the handle has been designed and manufactured by the author using 3D printing and resistant polystyrene. Due to its malleable composition, it absorbs small deviations and adapts to the handle for a good grip. One of the perception cameras that generates the information in the form of a point cloud that will be processed to detect the handle is located on the grip itself.

Fig. 3 shows the schematic with all the sensors and hardware devices installed in the robot that provide a robust, safe and reliable system.

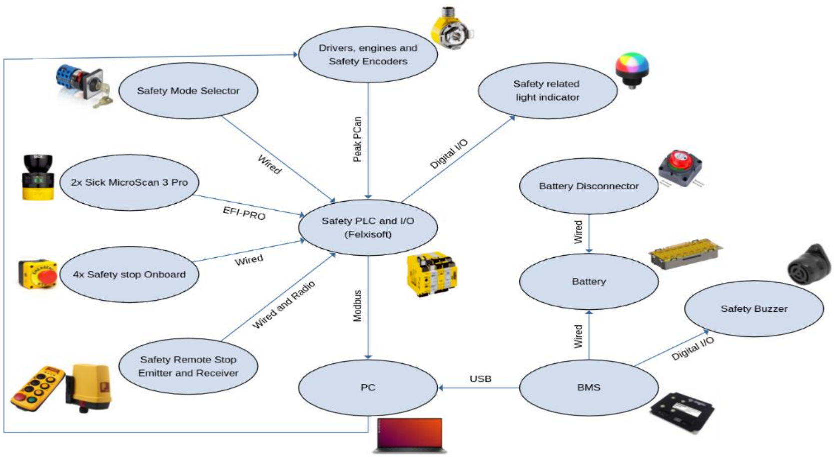

Fig. 3. Hardware configuration of the robot

1.3 AUTONOMOUS NAVIGATION

1.3.1 Global navigation

The navigation system uses a classical approach based on two phases: mapping and localization/navigation. In a first learning or mapping phase, *Simultaneous Localization and Mapping* (SLAM) is used [3] to generate a 2D occupancy map. Using the readings coming from the lasers, a contour-based metric cost map is generated.

In the second phase, the previously saved map is used to locate and generate traversable paths taking into account the dimensions of the robot. The localization is based on the Monte Carlo method (AMCL) of [4] which consists of a particle filter that computes the position of the robot probabilistically from a set of particles formed by representative samples of the possible state space. Assuming that each particle is a possible position of the robot in the plane, for each particle the probability that the robot is in that position is calculated. This is done by comparing what the robot perceives by its sensors with what it should perceive if it were in the position indicated by the particle (likelihood function).

For its part, the planner is responsible for two tasks: calculating safe routes along which the robot moves and sending speed commands to the drive controllers of the drive system to enable the robot to follow the calculated route.

Path planning is divided into global and local planning. Global planning calculates geometrically a route between the robot's origin point and the destination point. In this proposal, Dijkstra's algorithm is used. [5], which is implemented in the ROS package global_planner [6]. In turn, the local planner is in charge of two tasks: on the one hand, it computes the actual speed commands to follow the planned route and, on the other hand, it adapts the previous route to avoid obstacles not present at the time the global planner computed the original route. There are different local planning algorithms such as *dwa_local_planner*, *eband_local_planner*, being the *teb_local_planner* method the one used in this work. This ROS package [7] implements the *Timed Elastic Band* (TEB) approach [8], which attempts to optimize the original trajectory with bands that minimize trajectory execution time, obstacle clearance, and kinetic/dynamic constraint compliance. It is the most novel approach of those presented and allows for further configuration and tuning of the final robot behavior.

1.4 DOOR HANDLE DETECTION

A more detailed description of the algorithm for detecting the door and estimating the position and orientation of the handle would be as follows:

- Step 1: Detect the door.
    - Step 1.1.: Apply RANSAC for plane detection with 2 cm threshold distance and return the model with the highest support after 1000 iterations.
    - Step 1.2.: Segment the space between the result of step 1.1. and the robot using a density-based algorithm that requires a minimum distance of 2 cm between neighbors in the same cluster, and a minimum cluster size of 10 points.
    - Step 1.3.: Obtain the parallelepipeds of smaller volume that encompass the clusters obtained previously.
    - Step 1.4.: Eliminate those clusters in which the previous process returns parallelepipeds whose maximum dimension is not between 10 and 25 cm.
    - Step 1.5.: If the above process returns a single cluster, continue towards the estimation of the position and orientation of the handle. Otherwise, remove the detected plane from the point cloud and return to Step 1.1.
- Step 2: Estimate the position and orientation of the handle.
    - Step 2.1.: Calculate the mean of the color of the door elements, as well as the mean of the color of the elements in the cluster containing the handle and eliminate those elements in the cluster that are closer to the color of the door than to the color of the handle cluster.
    - Step 2.2.: Calculate the equations of two planes parallel to the door and at a distance of 50 cm, one in the space closest to the robot, and the other in the farthest one.
    - Step 2.3.: Project the handle cluster points on these planes.
    - Step 2.4.: For each of the two planes, calculate the parallelogram with the smallest area that encompasses the points projected on it.
    - Step 2.5: Calculate the minimum parallelepiped encompassing the parallelograms defined above, as well as the cluster of the handle.
    - Step 2.6: Reduce their dimensions in such a way that they do not include more points than those of the original cluster.
    - Step 2.7: Calculate the position of the handle attachment point from the obtained parallelepiped and previous knowledge of its geometry.
    - Step 2.8: Calculate the quaternion corresponding to the robot effector rotation so that it can perform the door opening.
- Step 3: Return the medoid of the quaternions obtained after performing steps 1 and 2 six times.

The Fig. 4 shows the target handle on which the coordinates of the optimal gripping point by the robot gripper have been marked.

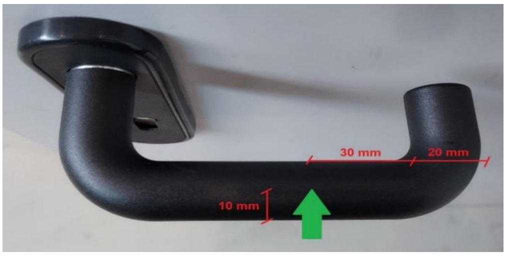

Fig. 4. Image of the handle showing the grip point.

1.5 HANDLE MANIPULATION

The schematic of the Fig. 5 shows the different modules of the application, as well as their connection to each other and to the manipulators themselves. The robotic arms are the new KUKA IIWA robotic arms, which provide a gravity compensation module [9] which facilitate the learning-by-demonstration task by counteracting the force of gravity and the weight of the arms and keeping them in a floating state. In that way, the person can teach the necessary movements for opening doors in a simple way. The data acquisition module collects the robot's parameters in real time and stores them in the database.

After the learning phase, when the robot opens the doors autonomously, it executes and monitors the saved trajectories that have been previously analyzed and filtered. In this way, the system knows at all times the state of the robot and the execution flow.

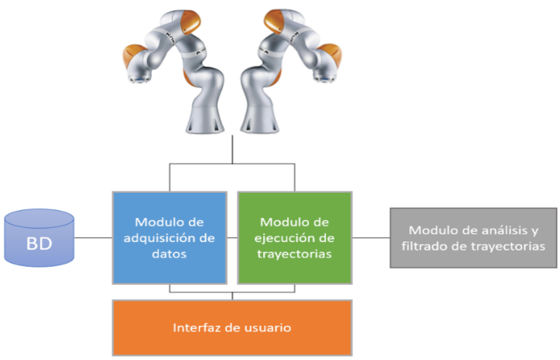

Fig. 5. Schematic of the learning-by-demonstration application.

Each of the modules involved in the task is detailed in more detail below.

- **Data acquisition:** Stores in its database information of the 6D position of the gripper and the state of the robot axes at a frequency of 10Hz. Additionally, this module uses an external reference source (e.g., a camera placed on the robot to try to find a marker in the environment) for the final position of the trajectory. This reference will allow to relocate and recalculate the trajectory in case the moving platform is not positioned exactly at the point where the learning was performed. In this application, the external reference will be the attachment point provided by the handle detection system.
- **Trajectory analysis and filtering:** Different filters to manage and modify trajectories, giving the possibility to adapt the nominal trajectories stored in the database to the specific needs of each run.

Among the different filters available, we find functionalities such as point down sampling or modification of the start or end of the trajectory.

- **Trajectory execution:** Capable of executing trajectories stored in the database, adapting the information to the needs of each execution. The main idea behind this module is to extract the main information of each trajectory, filtering possible inaccuracies and erratic movements introduced by the user during learning. The module executes the following steps:
    - If a marker is detected, transform the nominal trajectory to reference the new marker position.
    - Modify start or end of trajectory if necessary.
    - Down sampling of the trajectory positions, reducing the number of points while ensuring a maximum distance between them. This filter allows smoothing the trajectories, as well as eliminating small disturbances introduced by the user.
    - Analysis of inverse kinematics and continuity of the trajectory to ensure a safe execution of the trajectory, which is essential considering that the trajectory may have been modified by the different filters.
- **User interface**: to facilitate the use of the learning-by-demonstration tool, the application has an HTML5 user interface [10] that can be used from any device with a web browser. The interface is designed to guide the user through the process, offering an intuitive approach for non-expert users to generate new programs.

  As shown in Fig. 6the interface is very simple and easy to understand. It divides the modules into tabs where you can select:
    - *Teaching*: Learning module where you select the arm or arms to work with and to generate and store the trajectories. During this process, reference actions can be included as shown in the window on the right. Some of these actions can be: open and close valves, start or end compliance mode [11], trigger alarm, etc., even new user-generated actions can be added.
    - *Trajectories*: List with all stored trajectories. They can be filtered according to certain criteria. In addition, it shows the execution of the trajectory in a 3D environment.
    - *Execute Trajectory*: Allows you to select the joint group to be executed while defining the movement speed. Allows you to set whether there is an external reference input such as a marker or a detection system. After parameterization, it executes the trajectory with the selected group and the set parameters.
    - *Execute Compliance*: Analogous to the previous system with the addition of the activated *compliance* system, which is required for certain critical applications.

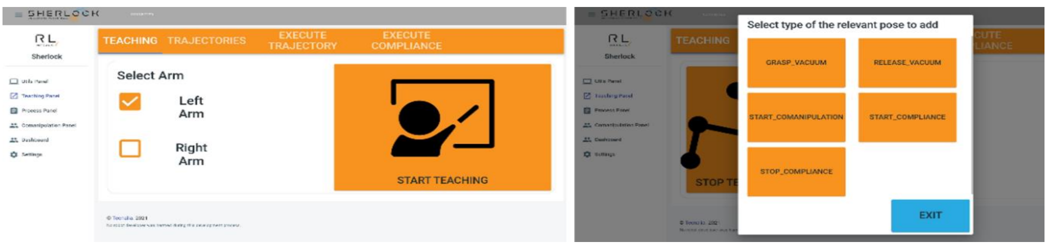

Fig. 6. User interface for learning by demonstration.

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10 Dual arm co-manipulation architecture with enhanced human–robot communication for large part manipulation

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Article

Dual Arm Co-Manipulation Architecture with Enhanced Human–Robot Communication for Large Part Manipulation

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Abstract: The emergence of collaborative robotics has had a great impact on the development of robotic solutions for cooperative tasks nowadays carried out by humans, especially in industrial environments where robots can act as assistants to operators. Even so, the coordinated manipulation of large parts between robots and humans gives rise to many technical challenges, ranging from the coordination of both robotic arms to the human–robot information exchange. This paper presents a novel architecture for the execution of trajectory driven collaborative tasks, combining impedance control and trajectory coordination in the control loop, as well as adding mechanisms to provide effective robot-to-human feedback for a successful and satisfactory task completion. The obtained results demonstrate the validity of the proposed architecture as well as its suitability for the implementation of collaborative robotic systems.

Keywords: human–robot interaction; co-manipulation; human–robot interface; assistant robots

1. Introduction

The emergence of collaborative robotics changed the development of robotic solutions drastically for cooperative tasks. Industrial environments offer an interesting scenario for collaborative robotics, an environment where robots could act as assistants to operators [1,2], helping them in their usual tasks. Even so, the successful development of cooperative operations between the operators and robots gives rise to many challenges. Beginning from the low-level robot control [3] and ending with the social and acceptance aspects of these kinds of applications [4], many facets must be tackled during the implementation phase.

In cooperative manipulation tasks, one key aspect which is shared among almost all of them is the exchange of implicit and explicit information between both actors. For example, two operators are able to transport and place large parts with few or no visual information of their partner, using mainly the feedback of the forces sensed during the manipulation to adapt their trajectories and fulfill the task, adding extra information only when required. Even so, it is important choosing the most suitable cues for this information exchange to ensure successful completion of the task.

This paper presents a dual arm co-manipulation architecture for large part manipulation with enhanced human–robot communication capabilities. The proposed approach is based on three key elements: (1) Human driven co-manipulation, (2) coordination of dual arm robots and adaptation of trajectories to unexpected events, and (3) robot-to-human feedback for successful task completion.

The presented architecture tackles these three elements, defining a new scheme for dual arm co-manipulation tasks. This architecture pays special attention to the psychological aspects of the task, which is reflected in the inclusion of user studies in the architecture design and development phase. The implementation and testing of the architecture shows its suitability for cooperative industrial applications.

The paper is organized as follows. Section 2 provides information about related work. Section 3 presents the proposed architecture. Details about the low-level robot control and coordination are provided in Section 4. Section 5 gives information about data management for feedback generation. Section 6 presents the process carried out in the development of the *user interface*. Details about the implementation of the architecture are given in Section 7. Finally, Section 8 contains information about the conclusions and future work.

2. Related Work

Human–robot manipulation is a recurrent research topic, with multiple scenarios and approaches proposed. From classical scenarios with standard robotic manipulators [5], to the appearance of humanoid robots [6], many works about co-manipulation can be found in the literature.

Within the different topics posed in human–robot collaboration, force control is one of the most studied fields, with many approaches and algorithms to take advantage of the force based interaction. Lichiardopol et al. [3] propose a control scheme for human–robot co-manipulation with a single robot, where the system estimates an unknown and time-varying mass as well as the force applied by the operator. Dimeas and Aspragathos [5,7] pose a method to detect unstable behavior and stabilize the robot with an online adaptation of the admittance control gains, adding reinforcement learning to estimate parameters for effective cooperation. Peternel et al. [8] propose an approach for co-manipulation tasks such as sawing or bolt screwing through a human-in-the-loop framework which integrates online information about the human motor function and manipulability properties.

The use of Artificial Intelligence also helps improving co-manipulation applications, adding mechanisms to tune and optimize control models. Su et al. [9] propose the use of a recurrent neural network (RNN) to perform the trajectory control of redundant robot manipulators. Roveda et. al. [2,10] also propose the use of a neural network to optimize the control parameters, implementing a cooperative fuzzy-impedance control with embedded safety rules to assist human operators in heavy industrial applications while manipulating unknown weight parts. Moreover, Deep Learning algorithms have also been used for the identification of robot tool dynamics [11], allowing a fast computation and adding noise robustness.

Additionally, the use of predefined trajectories and guides for dual arm and co-manipulation tasks appear in different research works. Gan et al. [12] present a position/force coordination control for multi-robot systems where an object-oriented hierarchical trajectory planning is adopted as a first step of a welding task. Jlassi et al. [13] introduce a modified impedance control method for heavy load co-manipulation where an event controlled online trajectory generator is included to translate the human operator intentions into ideal trajectories. Following the topic of trajectory generation, Raiola et al. [14] propose a framework to design virtual guides through a demonstration using Gaussian mixture models.

Even so, few approaches include human and social factors in the system design. From the user point of view any new technology needs to be accepted by the workforce to be effective. Lack of trust can be caused by a lack of transparency in robot behaviour as shown in the work of Sanders et al. and Wortham and Theodorou [15,16]. People are likely to feel more comfortable and confident working with a robot if they know how it behaves and can anticipate what it will do next. In fact, Hayes and Scassellati [4] suggest that efficient communication between humans and robots is impossible without mutual understanding of each other behavior and appropriate expectations.

The robot's action, communication, and transparency not only can increase task performance according to Lakhmani et al. [17], but operators' well-being in terms of mental workload and situation awareness as noted by Hayes and Shah [18]. Furthermore, Sanders et al. [15] propose that a consistent and constant flow of information can have a positive impact on trust. Trust is essential for efficient task completion; according to Wright et al. [19], too little trust can result in technology rejection, while too much trust can lead to complacency. In situations with low levels of trust, mental workload and cognitive demand increase due to monitoring of the robot's performance. Such increases result in less cognitive capacity left for monitoring the environment and complying with safety procedures as shown in Chen et al. and Saxby et al. [20,21]. In general, robot behavior transparency can have impacts on individual performance, trust, mental workload, and user experience. Studies establishing recommendations for human robot interaction and communication should assess these factors.

As an example of the previously exposed importance of the human factors, Weiss et al. [22] present a work where case studies are conducted during the use and programming of collaborative robots in industrial environments, adding an anthropocentric dimension to the work.

3. Proposed Architecture

As posed in the introduction, the aim of the presented work is to develop a dual arm robotic system able to assist human operators in manipulation tasks with large parts. The collaborative nature of this manipulation task raises many challenges, making it necessary to tackle different aspects ranging from robot control to human–robot interaction. In this sense, the presented work pays special attention to the human factors of the task in order to include the most suitable cues for an efficient and understandable information exchange between robot and human.

In the first step of the development, the large part transportation process has been analyzed in order to understand how humans perform it and extract the basic elements of the task, as well as the requirements to be transferred to the robot:

- During the transportation of large parts by humans, both actors agree (implicit or explicitly) on an approximate trajectory, which will be the basis for the transportation process. Following this premise, robots will manage a *nominal trajectory* which can be manually defined by users or generated automatically (e.g., using artificial vision).
- When humans transport large parts along a previously agreed path, any of them are able to deform this *nominal trajectory* in order to adapt the process to any unexpected event. In these cases, both actors are able to adapt their movements in a coordinated way without any prior knowledge, just based on the sensed forces. The implementation of *impedance control* [23,24] is proposed to mimic this behavior.
- The premise of this implementation is that robots act as assistants to the human. Taking this into account, robots will only advance in a trajectory when the operator moves the part along the defined path. Therefore, the operators will always play a master role in the co-manipulation task.
- As we are working with a dual arm robotic system, both arms need to move with a degree of coordination. Even so, this coordination will not be totally tight as in traditional robotics, as large part manipulation may require the adaptation of both robots due to uncertainties like the deformation of the objects or the human factor.
- During the part manipulation, besides the force feedback, humans exchange additional feedback as voice commands or gestures. It will be necessary to investigate how to include these cues in the robotic system.

To fulfill the previously presented requirements, a three-layer architecture is proposed:

- **Guidance Control Layer:** This initial layer is in charge of the low-level control of the robots, implementing a *Trajectory Driven Guidance with Impedance Control*.
- **Guidance Information Management Layer:** This second layer collects real time data of the *Guidance Control Layer* and generates meaningful information to be used as robot-to-human feedback.
- **User Interface Layer:** This last layer is the one in charge of presenting the guidance feedback to operators, using different cues to this end.

This three-layer architecture allows the co-manipulation task to be performed, devoting specific modules to the control of the dual arm robot control and to the preparation and presentation of information for human–robot interaction. It covers all functionality from low-level control to high-level interaction feedback. Figure 1 illustrates the presented architecture.

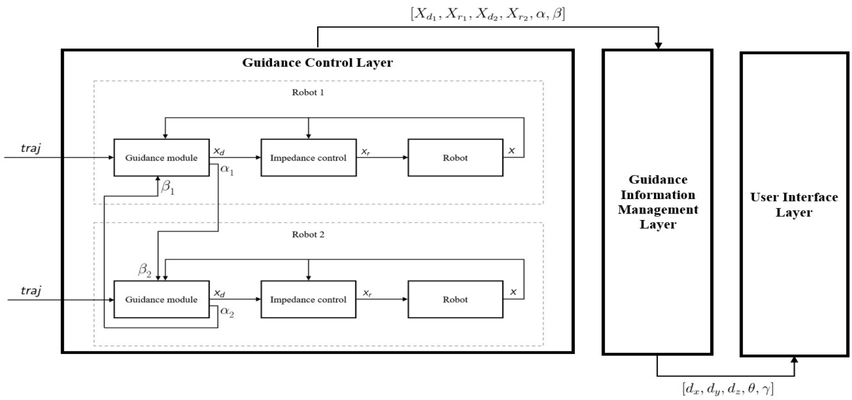


Figure 1. Architecture for dual arm co-manipulation.

The following sections provide further information about the different layers and their features.

4. Guidance Control Layer

The aim of this initial layer is to implement a control algorithm that allows the addition of a nominal trajectory to the impedance control while maintaining the coordination between two robot arms.

The main idea of the algorithm is to follow a provided trajectory as an operator guides the robot: the robot will transport the part smoothly along the trajectory while the robot will increase the resistance in the directions orthogonal to the nominal path. Additionally, impedance control is added to allow deformations on the path. It will provide some freedom to deform the robot path to the user as long as it guides the robot near the nominal trajectory. Besides the impedance control parameters, a set of trajectory points will also be used as input, points that will be linearly interpolated to generate the paths.

Specifically, the algorithm implements a two step control scheme for each robot. In a first step, the *Guidance module* calculates the next trajectory pose $\boldsymbol{X}_d$ based on the nominal trajectory, current robot pose, and percentage of trajectory covered by both arms. In a second step, the *Impedance control module* modifies this pose in order to obtain a compliant behavior, calculating reference pose $\boldsymbol{X}_r$.

The following sections provide information about the *Guidance module* and *Impedance control module*. Further details on this algorithm can be found in the work of Ibarguren et al. [25].

4.1. Guidance Module

The initial module of the control algorithm is based on a *Trajectory Driven Guidance with Impedance Control* and is in charge of calculating the set point sent to the *Impedance control module*. Based on a set of trajectory poses provided as input to the algorithm, it iterates along with the different segments of the trajectory. Specifically, these are the steps followed by the control algorithm to define the next set point (theoretical pose of each robot arm) in each loop based on an initial segment pose $\boldsymbol{A}$ and the end segment pose $\boldsymbol{B}$:

- Project the current robot pose $\boldsymbol{X}$ in the vector $\overrightarrow{\boldsymbol{X}_d^i \boldsymbol{B}}$, where $\boldsymbol{X}_d^i$ is the current setpoint and $\boldsymbol{B}$ is the end of the current segment of the trajectory.

$$\overrightarrow{\boldsymbol{P}} = \frac{\overrightarrow{\boldsymbol{X}_d^i \boldsymbol{X}} \cdot \overrightarrow{\boldsymbol{X}_d^i \boldsymbol{B}}}{|\overrightarrow{\boldsymbol{X}_d^i \boldsymbol{B}}|^2} \overrightarrow{\boldsymbol{X}_d^i \boldsymbol{B}} \tag{1}$$

- At this step, the corrected advance vector $\overrightarrow{\boldsymbol{P}_c}$ is calculated using the projection vector $\overrightarrow{\boldsymbol{P}}$ and correction factor μ. It allows reducing the advance when the robot's trajectory coverage is above the other robot's, and increasing this advance otherwise.

$$\overrightarrow{\boldsymbol{P}_c} = \mu \overrightarrow{\boldsymbol{P}} \tag{2}$$

  The correction factor μ is calculated using values α, β, and λ, where α is the percentage of the trajectory covered by the robot arm, β is the percentage of the trajectory of the other robot arm, and parameter λ allows to tune this correction factor, adjusting the increase and decrease rate. If λ takes high values, the robot that has covered less trajectory percentage will be boosted (a maximum μ of 2) while the robot with greater trajectory percentage covered will be dampened (a minimum μ of 0). Otherwise, if λ is set to 0, there will not be any kind of coordination between the robots and the value of μ will always be 1.

  Additionally, the direction of the projection vector $\overrightarrow{\boldsymbol{P}}$ is checked; if the vector points backwards the correction factor μ is set to 0 to avoid reverse movements.

$$\mu = \begin{cases} 0, & \text{if} \quad \overrightarrow{\boldsymbol{P}} \cdot \overrightarrow{\boldsymbol{X}_d^i \boldsymbol{B}} < 0 \\ 2 - \frac{2}{1+e^{-\lambda(\alpha-\beta)}}, & \text{otherwise} \end{cases} \tag{3}$$

- The new translation vector $\overrightarrow{\boldsymbol{X}_d^{i+1}}$ is calculated as

$$\overrightarrow{\boldsymbol{X}_d^{i+1}} = \overrightarrow{\boldsymbol{X}_d^i} + \overrightarrow{\boldsymbol{P}_c} \tag{4}$$

  while quaternion Q^{i+1} is interpolated between the rotations of poses $\boldsymbol{A}$ and $\boldsymbol{B}$ using the *spherical linear interpolation* [26] as

$$Q^{i+1} = SLERP(Q_A, Q_B, w) \tag{5}$$

$$SLERP(Q_A, Q_B, w) = Q_A\ exp(w\ log(Q_A^{-1}\ Q_B)) \tag{6}$$

  where w is calculated as

$$w = \frac{|\overrightarrow{\boldsymbol{A}\boldsymbol{X}_d^{i+1}}|}{|\overrightarrow{\boldsymbol{A}\boldsymbol{B}}|} \tag{7}$$

- Finally, the desired set point $\boldsymbol{X}_d$ is composed using translation vector $\overrightarrow{\boldsymbol{X}_d^{i+1}}$ and rotation matrix $\boldsymbol{R}^{i+1}$ created from quaternion Q^{i+1} as

$$\boldsymbol{X}_d = \left[\begin{array}{c|c} \boldsymbol{R}^{i+1} & \overrightarrow{\boldsymbol{X}_d^{i+1}} \\ \hline 0 & 1 \end{array}\right] \tag{8}$$

  This new pose $\boldsymbol{X}_d$ is sent to the *Impedance control module* to be used as the set point.

4.2. Impedance Control Module

In the second step, a compliant Cartesian behavior is added to each robotic arm implementing Cartesian impedance control [27,28]. The *Impedance control module* allows to establish a mass–damper–spring relationship between the Cartesian position Δx and the Cartesian force $\boldsymbol{F}$, the following formula is applied,

$$\boldsymbol{F} = \boldsymbol{M}\Delta\ddot{x} + \boldsymbol{D}\Delta\dot{x} + \boldsymbol{K}\Delta x, \tag{9}$$

where $\boldsymbol{M}$, $\boldsymbol{D}$, and $\boldsymbol{K}$ represent the virtual inertia, damping, and stiffness of the system, respectively.

To calculate the reference pose $\boldsymbol{X}_r$, based on the previously calculated set point $\boldsymbol{X}_d$ and the sensed force vector $\boldsymbol{F}$,

$$\boldsymbol{X}_r = \boldsymbol{X}_d - \frac{\Delta \boldsymbol{F}}{\boldsymbol{M}\Delta t^2 + \boldsymbol{D}\Delta t + \boldsymbol{K}}, \tag{10}$$

where $\Delta\boldsymbol{F}$ represents the difference between the desired contact force and the actual one.

This pose $\boldsymbol{X}_r$ is sent to the robot for the execution of the dual arm co-manipulation trajectory.

5. Guidance Information Management Layer

As stated previously, this second layer collects real time information from the *Guidance Control Layer* and manages it in order to generate meaningful information to be used as robot-to-human feedback. Therefore, this step converts raw information provided by the control layer into human-understandable data.

The *Guidance Information Management Layer* receives input vector $\boldsymbol{G}$ containing the following values,

$$\boldsymbol{G} = [\boldsymbol{X}_{d_1}, \boldsymbol{X}_{r_1}, \boldsymbol{X}_{d_2}, \boldsymbol{X}_{r_2}, \alpha, \beta], \tag{11}$$

where $\boldsymbol{X}_{d_1}$ and $\boldsymbol{X}_{d_2}$ represent the set point of each robot, $\boldsymbol{X}_{r_1}$ and $\boldsymbol{X}_{r_2}$ define the reference pose of both robots after applying the Cartesian impedance control, and α and β are the trajectory percentage covered by the robots.

Based on this information, this layer calculates metrics about the deviation in the trajectory, quality of the guidance and the overall trajectory percentage covered. Specifically, the trajectory deviation $\boldsymbol{D} = [d_x, d_y, d_z]$ is calculated as

$$\boldsymbol{D} = [d_x, d_y, d_z] = \frac{(\overrightarrow{\boldsymbol{X}_{d_1}} - \overrightarrow{\boldsymbol{X}_{r_1}}) + (\overrightarrow{\boldsymbol{X}_{d_2}} - \overrightarrow{\boldsymbol{X}_{r_2}})}{2}, \tag{12}$$

where $\overrightarrow{\boldsymbol{X}_{d_1}}$ and $\overrightarrow{\boldsymbol{X}_{d_2}}$ represent the translation part of both setpoints and $\overrightarrow{\boldsymbol{X}_{r_1}}$ and $\overrightarrow{\boldsymbol{X}_{r_2}}$ are the translation part of the reference poses of both robots.

To quantify the quality of the guidance θ, the following equation has been defined,

$$\theta = \lambda_{traj}\, min\left(1, \frac{|\alpha - \beta|}{m_{traj}}\right) + \lambda_{dev1}\, min\left(1, \frac{\|\overrightarrow{\boldsymbol{X}_{d_1}} - \overrightarrow{\boldsymbol{X}_{r_1}}\|}{m_{dev}}\right) + \lambda_{dev2}\, min\left(1, \frac{\|\overrightarrow{\boldsymbol{X}_{d_2}} - \overrightarrow{\boldsymbol{X}_{r_2}}\|}{m_{dev}}\right), \tag{13}$$

$$\lambda_{traj} + \lambda_{dev1} + \lambda_{dev2} = 1 \tag{14}$$

where values m_{traj} and m_{dev} are the maximum trajectory percentage difference and trajectory deviation allowed, respectively, acting as a threshold. Values λ_{traj}, λ_{dev1}, and λ_{dev2} are weighting factors that allow defining which of the measures (trajectory percentage difference or trajectory deviation of each robot) have more impact in the quality of the guidance. Therefore, the equation will provide a value ranging from 0 to 1, where 0 indicates a perfect trajectory guidance and 1 indicates a guidance error over the limits set through the different parameters.

Finally, the mean of the covered trajectory percentage γ is calculated as

$$\gamma = \frac{\alpha + \beta}{2}. \tag{15}$$

These previous equations will calculate vector $\boldsymbol{U}$ as

$$\boldsymbol{U} = [d_x, d_y, d_z, \theta, \gamma], \tag{16}$$

where values d_x, d_y, and d_z contain information about the guidance deviation; θ defines the quality of the guidance process; and γ is the mean trajectory percentage covered during the process.

This vector $\boldsymbol{U}$ is the data that will be used as input in the *User Interface Layer* to generate the appropriate cues for the robot-to-human interaction and feedback.

6. User Interface Layer

Information communication is one of the essential factors for developing successful human–robot interaction. Therefore, this *User Interface Layer* aims to provide an interface able to generate suitable and understandable cues to communicate the status of the co-manipulation task. Although some research suggests that modality of information communication (audio, text, and graphic) does not affect trust and user experience as shown in [15], Selkowitz et al. [29] have found that the use of a graphic information display does not significantly increase user workload. In addition to possible positive effects on workload, the graphic modality has the benefit of requiring little experience and training to use [30], and it can be beneficial for people with different information processing abilities due to, for example, dyslexia as discussed in [31]. Another advantage is that, in most cases, universally understood symbols can be used to provide support to people from different countries and cultures as considered by Ben et al. [32].

To identify and select the most effective and understandable cues, two user studies were carried out. These studies will help in the development and design of the *user interface* as they will identify the most effective way of presenting the information generated in the *Guidance Information Management Layer*. The psychological and performance impact of the developed human–robot collaboration communication was investigated over these two studies.

In the initial phase of the user interface design process, a number of possible cues were identified. Individuals in a team communicate by gaze and non-verbal communication [33,34] and to replicate this, the current study used an avatar representing the robot and added head movements to indicate trajectory deviation. In addition, trajectory deviation and trajectory percentage parameters were introduced as graphical symbols dynamically providing information about the task to the user. Finally, the user interface display used a background with a universally known paradigm of a traffic light to establish how far from the optimal path the robot is (from green color indicating on an optimal path to red indicating a strong deviation).

The following sections provide further details about the two user studies.

6.1. User Study 1

The main aim of *User Study 1* was to investigate which user interface is the most effective in indicating the robot behavior and how these user interfaces can be improved. To achieve this aim, six versions of the user interface were used in an online study with qualitative and quantitative questions. Six experimental conditions in the form of 20 s video clips of an operator and a robot collaborating were presented to all participants in a counterbalanced order. The six different visual user interfaces indicating what the robot is communicating to the operator are presented in Figure 2 from top left to bottom right as follows.

- Full body avatar and background color (A)
- Avatar torso and background colour (B)

- Background colour (C)
- Dashboard, full body avatar and background color (D)
- Dashboard, avatar torso and background colour (E)
- Dashboard and background colour (F)

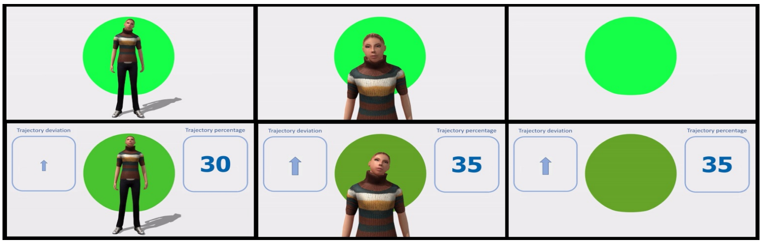


Figure 2. Six tested user interfaces.

The study collected quantitative and qualitative data. The quantitative question asked participants to rate user interface clarity on a scale from 0 "Extremely unclear" to 100 "Extremely clear". This question was split into several sub-parts on each of the core elements of the user interface depending on the condition (avatar face, avatar posture, background, trajectory deviation, and percentage deviation). The mean of the answers for each core element was calculated to produce an overall clarity rating. The data had a normal distribution and was further analyzed with a repeated measures ANOVA. The qualitative questions asked the participants to describe what they thought the user interface was trying to communicate to the operator and how it could be clarified. Twenty-eight participants provided qualitative responses for open-ended questions; however, only 18 of them answered all the quantitative questions allowing further inferential analysis. Eleven participants indicated their gender as male, five as female, three reported as "other", and nine did not answer the question. The average age of participants was 33.11 years (SD = 9.49) with ten participants not providing their age. Three participants reported they came from the manufacturing industry, twelve from an academic environment, one from "other—construction", while ten did not respond where they were working. The study was approved by the Cranfield University Research Ethics Committee.

The user interface information clarity was significantly different between conditions $(F(2.37, 85) = 8.80,\ p \leq 0.001)$. Post hoc comparison with Bonferroni correction between conditions indicated that the clarity was significantly higher for the Dashboard and background color (F) user interface compared to all user interfaces with an avatar, but there was no significant difference with the Background (C) user interface (Table 1). On the other hand, the Avatar torso and background color (B) user interface was rated significantly lower on clarity compared to all other conditions except the Full body avatar and background color (A) and the Dashboard, full body avatar, and background color (E) user interfaces (see Table 1 for the significance levels of all comparisons).

Looking at the participants' preferences, 75% of participants preferred the user interface with only the Dashboard and background (F), 15% preferred the Dashboard, avatar torso and background color (E), 5% preferred only the Background (C) and 5% preferred the Avatar torso and background color (B). The full body size avatar (with or without dashboard (A and D)) was not chosen by any participant as a preferred user interface.

Table 1. Post hoc statistics and descriptive information between all experimental conditions.

	Avatar Torso and Background	**Dashboard, Avatar Torso and Background**	**Dashboard and Background**	**Background**	**Full Body Avatar and Background**	**Dashboard, Full Body Avatar and Background**
Avatar torso and background		$p = 0.043$	$p = 0.007$	$p = 0.025$	$p \geq 0.999$	$p = 0.072$
Dashboard, avatar torso and background			$p = 0.021$	$p \geq 0.999$	$p = 0.463$	$p \geq 0.999$
Dashboard and background				$p \geq 0.999$	$p = 0.018$	$p = 0.034$
Background					$p = 0.017$	$p \geq 0.999$
Full body avatar and background						$p = 0.378$
Mean (SD)	20.63 (4.11)	31.42 (4.95)	45.85 (6.82)	42.39 (7.63)	21.87 (4.28)	31.27 (4.49)

To shed some light on participant ratings on user interface clarity, participants' answers to the open-ended questions were analyzed further:

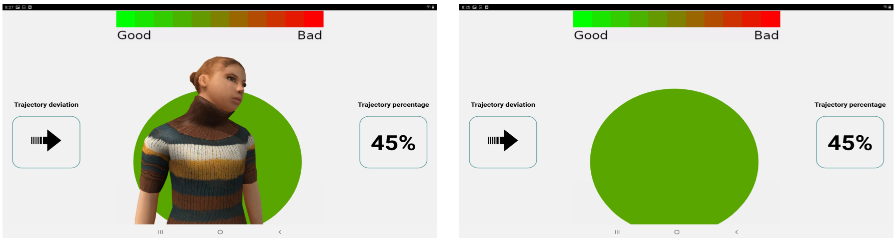
- Participants' opinions about the use of the avatar were split: Some participants appreciated that the avatar "makes (it) more comfortable to interact with a robot", other participants expressed dissatisfaction with it: "I already have my partner that bosses me around at home, I don't need another one in the workshop". Participants communicated that having only the avatar torso was more useful than the full body size avatar as the legs do not convey any task related information. Furthermore, the avatar's head movements were subtle and not all participants understood/noticed them; therefore, for future development more pronounced head movements were suggested.
- In relation to the other user interface features, participants indicated that the background circle should be accompanied by a benchmark scale indicating trajectory from "good" to "bad".
- Participants also commented that it might be useful to introduce commands or a feedback display to keep the communication less ambiguous. Some of the participants indicated that this could be done via audio feedback to the user.

These suggestions were included in the user interface in *User Study 2*.

6.2. *User Study 2: Laboratory Results*

Two types of the user interface were selected from *User Study 1* and adjusted according to the participant suggestions; specifically, the dashboard with the avatar (torso) (Figure 3a) and the dashboard without the avatar (Figure 3b). The two user interfaces included the following cues:

- Dashboard with the deviation from the trajectory and trajectory percentage.
- Avatar with head movements to indicate the deviation from the trajectory.
- Background color indicating the deviation from the trajectory.
- Voice commands indicating deviations from the trajectory.



(**a**) (**b**)

Figure 3. User interfaces for *User Study 2*. (**a**) The dashboard with the avatar (torso) (**b**) The dashboard without the avatar.

The main aim of *User Study 2* was to determine how the selected user interfaces affect collaborative task performance and participant well-being. The task required the participant and the robot to collaboratively remove a component from a shelf and place it in a fixture on the desk and then move back to the shelf (Figure 4). Thirteen participants took part in the study of which ten were males, two were females and one did not indicate their gender. The average age was 36.85 years (SD = 7.65). Seven participants indicated that they work with robots every day, two on a regular basis, three responded that they work with robots sometimes but not on a regular basis, and one participant said that they have never worked with robots. All participants took part in all conditions: two experimental conditions and the control condition with no user interface. The conditions were counterbalanced and the study assessed behavioral parameters (deviation from the optimal path and time to complete the tasks), and collected self-report data (Trust in Industrial Robot [35], NASA TLX [36], and User Experience Questionnaire [37]). This paper will focus on the behavioral and the User Experience Questionnaire results as the NASA TLX and Trust in Industrial Robot scales did not indicate any significant differences ($p > 0.05$). Additional qualitative questions relating to the user interface focused on what participants found the most useful for task completion and their suggestions for improvement of user interface clarity. The study was approved by the Cranfield University Research Ethics Committee.

Figure 4. Transporting a carbon fiber part from fixtures to shelf during *User Study 2* experiments.

To investigate how different user interfaces affect human performance efficiency, the mean task completion time and the mean deviation from the optimal trajectory were compared between conditions with a nonparametric Friedman's ANOVA as the data was not normally distributed.

The mean task completion time was measured in seconds. The analysis showed a trend difference in the mean deviation ($X^2(2) = 4.77, p = 0.092$), but no significant difference in the completion time ($X^2(2) = 0.15, p = 0.926$), see Table 2. Further investigation was performed on the mean deviation from the optimal trajectory which showed a lower deviation in the avatar condition compared to the control condition at a trend significance level ($Z = 1.71, p = 0.090$), but the differences between the no-avatar condition and the control condition or the avatar and the no-avatar condition were not significant ($Z = 1.36, p = 0.185$) and ($Z = 0.14, p = 0.906$).

Table 2. Means (SD) across three experimental conditions on the behavioral and user experience questionnaire measures.

	Control		Avatar		No-Avatar	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Behavioral data						
Completion time (sec)	42.71	10.74	45.57	12.56	43.85	11.68
Mean deviation	46.58	12.08	39.69	7.30	42.15	13.18
User Experience Questionnaire						
Attractiveness	1.45	0.69	1.58	0.98	1.70	0.78
Perspicuity	1.77	0.85	1.42	0.97	1.77	0.75
Efficiency	0.92	0.71	0.98	0.88	1.24	0.86
Dependability	1.17	0.70	1.19	0.74	1.60	0.67
Stimulation	1.56	0.46	1.3	1.10	1.67	0.74
Novelty	1.50	0.87	1.77	0.89	1.71	0.97

Finally, the subjective evaluation of participants' experience was measured with the User Experience Questionnaire (UEQ). Although the results were not significant ($X^2(5, 20.84) \leq 1.62, p \geq 0.200$), the score means across the factors between the conditions indicate that participants evaluated the user interface without the avatar relatively higher than the other interfaces, while the user interface with the avatar scored highest on the novelty factor. It is important to indicate that the control condition and the user interface with the avatar both ranked below average on the efficiency factor (Figure 5).

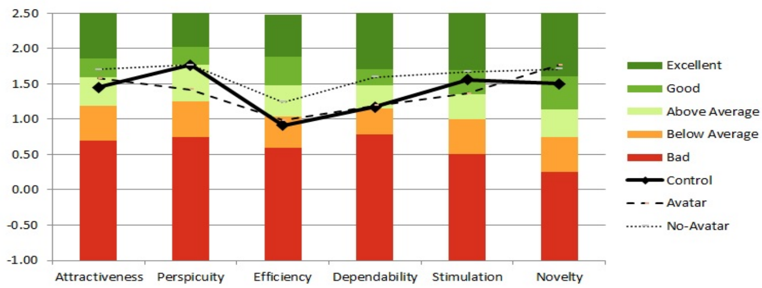


Figure 5. Reported user experience across six UEQ factors as a function of the experimental condition.

In their qualitative feedback, 38% of the participants indicated that audio information was the most useful and another 38% of the participants indicated the trajectory deviation and trajectory percentage were the most useful. Fifteen percent of the participants indicated that they would include depth information for the trajectory deviation, one participant asked for more detailed audio information to guide the movement, while another participant explained that they used mainly audio information to complete the task. Fifteen percent of the participants indicated that they did not use the avatar during the task as, according to them, it did not provide useful information. This qualitative information confirms the User Experience Questionnaire results indicating that participants found the user interface with trajectory deviation and trajectory percentage the most useful. However, behavioral information from the task suggest that the presence of the avatar can reduce the deviation from the optimal trajectory.

Based on the obtained results, it was decided to maintain both user interfaces in the presented robotic system, allowing the operators to choose between both options based on their preferences.

7. Implementation

The proposed robotic system has been implemented using a setup of two *Kuka LBR iiwa* robots with a payload of 7 kg for each arm, mounted on a mobile platform. The mobile manipulator includes an additional PC connected to both robot controllers. The robots are equipped with automatic tool exchangers and vacuum cups to allow grasping different types of large objects and parts. An additional IO module is also available to manage the tool exchangers as well as the suction of the vacuum cups. Figure 6 shows the set-up of the robots.

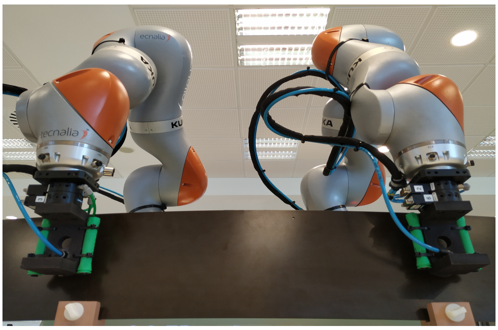


Figure 6. Set-up with two Kuka LBR iiwa robots.

A tablet has been used as interface for the guidance system. The selection of a tablet allows the mobility required for this kind of applications, as operators can transport it and place it in the most suitable placement for each co-manipulation task.

From the software point of view, all the computation of the *Guidance Control Layer* has been implemented in Java in the robot controllers. The *Impedance control module* makes use of Kuka Sunrise's Smart Servo library to close the control loop. Additionally, the external PC acts as bridge between both robots by means of several custom ROS nodes written in C++ which manage the connections and exchanges the trajectory information. Besides, this same PC runs the *Guidance Information Management Layer* as well as the *User Interface Layer*, which acts as HTML5 server providing the web interface to the tablet.

Finally, the tablet only acts as user interface, displaying the different cues based on the values sent from the external PC using any web browser installed on it. The implementation allows the use of multiple devices at the same time, therefore it could be possible to include several operators interacting with the robot at the same time.

8. Conclusions and Future Work

This paper presents a novel architecture for dual arm co-manipulation with an enhanced human–robot communication capabilities. The architecture addresses different aspects of a co-manipulation task, from the control algorithm to the user interface, paying special attention to the user experience and psychological aspects of the human–robot collaboration.

Initially, a control algorithm for the dual arm robots is presented, implementing a *Trajectory Driven Guidance with Impedance Control*. This algorithm allows guiding the robot along some virtual guides during the part transportation phase. The inclusion of an impedance control module adds flexibility as operators are able to deform the theoretical trajectory in order to face unexpected events or to correct errors.

Additionally, the architecture provides different modules to manage the information exchange between the robot and the human. The aim of these modules is to provide effective and understandable feedback for the completion of the part transport task. To improve the design of the user interface and select the most suitable cues, two *User Studies* have been carried out. The findings of both studies provide further insight on how a robot could communicate the task related information to the human. The user feedback on the clarity of the user interface, their needs and requirements to make the collaboration more transparent (Study 1) allowed to adjust the user interface and conduct a behavioral experiment (Study 2). The behavioral results of the actual human–robot interaction task show that the presence of the user interface has an impact on the performance, improving the precision of the guidance using the most suitable cues.

Even so, several aspects of the architecture can be further developed and improved as a future work. On the one hand, the impedance control parameters could be modified in execution time based on the human behavior in order to offer a more human-like manipulation experience. Furthermore, it would be interesting to add mechanisms to detect collisions (with external elements or between the robot arms) to ensure a safe human–robot interaction. On the other hand, suggestions made by participants in *User Study 1* and *2* could be implemented. These suggestions include presenting movement depth information or including the visual representation of the component, as well as recommendations to further develop audio information. Additionally, the inclusion of voice commands from operator to robot (e.g., to start/stop the guidance) would be an interesting addition to the co-manipulation tasks. The voice commands would be especially important during the manipulation of the large parts where it is difficult to use physical devices to input commands as parts need to be carried by both hands. Therefore, the inclusion of speech recognition and conversational agents would help to create a seamless human-to-robot interaction channel.

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