A Real-Time Stress Classification System based on Arousal Analysis of the Nervous System by an F-State Machine

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Abstract

Background and objective: Detection and labelling of an increment in the human stress level is a contribution focused principally on improving the quality of life of people. This work is aimed to develop a biophysical real-time stress identification and classification system, analysing two noninvasive signals, the galvanic skin response and the heart rate variability.

Methods: An experimental procedure was designed and configured in order to elicit a stressful situation that is similar to those found in real cases. A total of 166 subjects participated in this experimental stage. The set of registered signals of each subject was considered as one experiment. A preliminary qualitative analysis of the signals collected was made, based on previous counselling received from neurophysiologists and psychologists. This study revealed a relationship between changes in the temporal signals and the induced stress states in each subject. To identify and classify such states, a subsequent quantitative analysis was performed in order to determine specific numerical information related to the above mentioned relationship. This second analysis gives the particular details to design the finally proposed classification algorithm, based on a Finite State Machine.

Results: The proposed system is able to classify the detected stress stages at three levels: low, medium, and high. Furthermore, the system identifies persistent stress situations or momentary alerts, depending on the subject's arousal. The system reaches an F_1 score of 0.984 in the case of high level, an F_1 score of 0.970 for medium level, and an F_1 score of 0.943 for low level.

Conclusion: The resulting system is able to detect and classify different stress stages only based on two non invasive signals. These signals can be collected in people during their monitoring and be processed in a real-time sense, as the

system can be previously preconfigured. Therefore, it could easily be implemented in a wearable prototype that could be worn by end users without feeling to be monitored. Besides, due to its low computational, the computation of the signals slopes is easy to do and its deployment in real-time applications is feasible.

Keywords:

Stress, HRV, GSR, Finite-state machine.

1. Introduction

Nowadays, the study of stress in persons is an issue of high relevance into the research community, due to its effect in our society, as it has great influence on the health and the wellness of human beings. Focused on this issue, our multidisciplinary research group, composed of engineers, neuro-physiologics, medicals and people from the assistive field, has set as one of the main objectives to detect, identify and classify the different stress levels that a person lives in stressful situations. This proposal could be applied in fields as different as emotional intelligence, where emotion recognition has an important role [1,2], or in medicine, where disorders into the Autonomous Nervous System (ANS) needs being identified [3], trying to improve the quality of life of people, especially in persons with disabilities or some form of disease [4,5].

Therefore, a key issue to be investigated is how emotional responses to certain stress events occur in people. Thus, it is necessary to classify them and to observe how they affect their personal autonomy, and hence, their daily life. To this end, this work performs a study focused on physiological signals that can be measured in a non-invasive way. This solution will be able to accurately identify, at the earliest possible moment, when an individual is facing an emotional block situation, and to generate the corresponding alert signals to his/her caregivers or relatives in these cases. The proposed system is performed by analysing data collected from several volunteers, which are non-disabled people, in order to establish a method to carry out into collectives of people with disabilities, later on.

When stress is defined as an adaptive mechanism, the first postulates concerning sympathetic activation proposed by Cannon are often cited [6]. Cannon established the term "arousal" for defining the activation of the nervous system when a person reacts to a situation that requires his/her attention: from stressful activities to danger episodes. Subsequently, lot of studies based on aforementioned Cannon theory extended these fundamentals to analyze how the nervous system reacts to emotional states and stressful tasks, demonstrating that the sympathetic activation response evolves in a similar way, as presented in the review of Kreibig [7].

In order to deal with any of these situations, the organism response consists of the activation of the body systems, basically into the Autonomous Nervous System (ANS) [8-12], resulting in a psycho-physiological change with the aim of maintaining the homeostasis.

It is necessary to take into account that faced with the same situation not everyone responds in the same way, considering that each person has a different perception of the stressful situation being faced. Thus, personal arousal is greater, the higher the risk level is perceived to be, and it lasts as long the person feels that the risk or danger persists [13].

In order to address how the arousal suffered by an individual leads into an activation level and how this person perceives a situation as a stressful episode, several authors have studied the way to identify and label them. In this sense, Selye [14] introduced the concept of General Adaptation Syndrome (GAS), otherwise known as the stress response. GAS involves three phases: Alarm Phase, Stage of Resistance, and Stage of Exhaustion. In addition, Selye [14] modeled that stress response, as shown in Fig. 1(a), presenting theoretically the three phases involved over time. Afterwards, in order to provide quantitative values to the different levels that the response can reach, Kim et al. [15] proposed a quantitative approximation of the GAS model, which presents a stress response consistent with this model. In this new approximation of GAS model, presented in Fig. 1(b), the shape of the graph is determined by slope of the response (α) and maximum capacity of the resistance to stress (β). The solution developed in this work is based on this approximation of GAS model, where the analysis of slopes will permit a classification of low, medium and high activation levels.

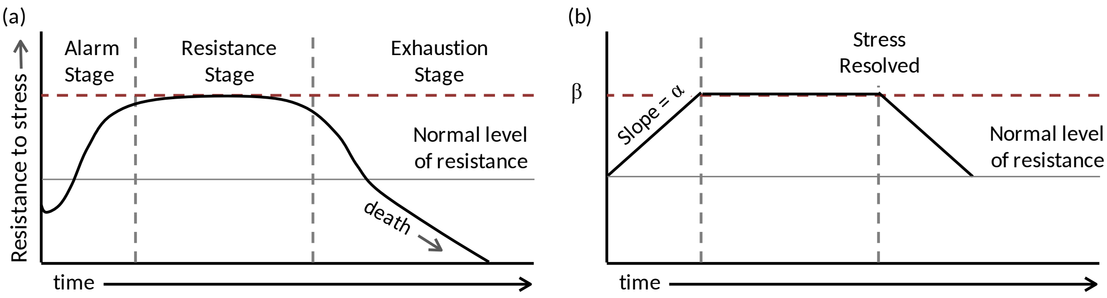


Fig. 1 - (a) General Adaptation Syndrome (GAS) model; (b) quantitative approximation of the GAS model

Furthermore, another relevant aspect to consider is how long the physiological perception of the stress is maintained. Among other studies, Ursin and Eriksen [16] presented a cognitive activation theory of stress, where they studied the duration of stressful situations and performed the labeling of such situations, dividing them into alerts and stress. Following this line, in this work we have evaluated how the activation levels appear and how long they remain, in order to distinguish between both situations, considering the latency of the activation and inhibition phases, as presented in the work of Ursin and Eriksen.

Considering the relationship between the body physiology and emotional states, the proper approach to identifying stressful situations appears to be the analysis of several physiological signals and the search for correlations between them. Several studies have tested the relationship between stress and physiological signals [2,17-24]. In this paper, we only use the galvanic skin response (GSR) and electrocardiogram (ECG) signals, since they give us enough information about the ANS functioning [3,12] and both can be collected with non-invasive wearable devices [17].

Most of the contributions based on the study of stress attempt to differentiate between stress and relaxation states, with the aim of identifying whether the individual is suffering a stress situation [19,20,23]. Therefore, in an effort to develop solutions for the analysis and detection of emotional changes generated by stressful situations, it is fundamental to be able to identify such changes precisely when they take place. The work presented in this paper studies how to carry out the detection of such stressful events, taking into account the detailed activation levels of the individual. The previous analysis was based on the works of Santos et al. [22] and Healy and Picard [24] incorporating a specific algorithm into the detection phase later on, which allowed the physiological signals to be processed in real time and provided a classification of the stress type detected.

There is a great diversity of techniques used to classify stress situations. In this work we will use state machines to detect stressful situations in real time. The application of this kind of technique provides an innovative aspect to this work, since specific examples using state machines to detect and classify stressful situations were not found in the bibliography. We adopted this technique due to its good results in the context of classification problems in other areas [25-29] and we hypothesised that this good behaviour could be transferred to our own work.

2. Materials and Methods

This section describes the selected methodology for this work, similar to previous works [22-24,30]. The development of this work begins with an experimental stage performed into a laboratory, where two non-intrusive physiological variables are measured from each subject.

From an initial experimental stage, two different databases are created: one related to the physiological signals measured, and a second with the behavioural data collected, both correlated in time. Considering collected information, data are divided in 2/3 and 1/3, in order to face design and validation phases, respectively.

Subsequently, the design phase is divided in three stages; a preliminary qualitative analysis, following by a quantitative analysis, and finally the design of a Finite State Machine (FSM), as shown in Fig. 2.

2.1 Experimental setup

There exist different proposals to elicit stressful situations into laboratories. The method of performing tasks is often used by researchers, as cited in the review by Alberdi et al. [30]. Among others, the most commonly used methods are “stop-signal tasks” [23], “stroop color-word” [23, 31], “arithmetical tasks” [32], and “puzzle tasks” [33,34], which our experiment belongs to.

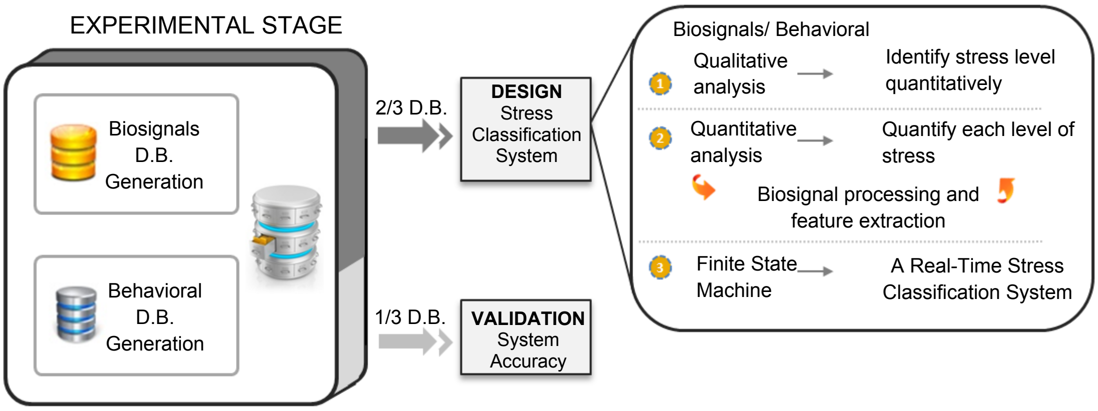


Fig. 2 - Development of a Real-Time Stress Classification System.

The experimental procedure used in this work was an innovative task with the aim of eliciting emotional changes in a group of volunteers leading to a stressful situation. This experimental phase was carried out in a controlled environment at the laboratory, and in a similar as possible way to a real situation. The challenge or stressful task proposed to the participants was the resolution of a 3D-wooden puzzle within a limited time.

During the experiment, physiological signal samples were collected, which were subsequently anonymised, to be further analysed in order to seek out stress patterns. As we mentioned, we only used GSR and ECG signals. In the signal analysis stage, instead of using ECG, the Heart Rate Variability (HRV) calculated from the ECG was used, as a measure of the time changes between each heart beat. HRV is a widely studied signal that reflects heart dynamics [35]. The physiological signals of the subjects were collected by the professional data acquisition system BIOPAC MP36 (Biopac Systems Inc., USA) at a sample rate of 1000 Hz. Biopac Acqknowledge 3.7.1 (Biopac Systems Inc., USA) was the software used for data acquisition and the units of GSR and ECG were microSiemen and volts respectively.

In the experimental stage, a total of 166 participants (125 males and 41 females), 19-45 years old (mean = 22.88, SD= 3.1) took part voluntarily. All the subjects were engineering students at the University of the Basque Country (UPV/EHU).

The subjects´ response analysis was carried out through three kinds of emotional assessment: notes and marks, a questionnaire and an interview. The first assessment method was with notes and marks (M), and they were inserted during the recording to mark specific episodes which enabled the identification of the time point when the stressful events occur, such as experiment onset, a piece of the puzzle falling, etc. The second one was a pictographic non-verbal questionnaire (Self-Assessment Manikin, SAM [36]) to evaluate emotional states in a dimensional way, which has been used in a large number of works due to its performance and appropriate evaluation [37,38]. In this questionnaire, emotions are classified into 3 dimensions (valence, arousal and dominance). For the third assessment method, participants underwent a short interview to find out how they had felt facing the different experiment phases.

For the experiment, a laboratory with 4 seats was prepared. On each seat there were an unsolved puzzle with its resolution, the documents to be completed and the necessary equipment for the collection of physiological variables (data acquisition system, a laptop, electrodes, transducers and wiring).

Participants stood waiting outside the laboratory and, once everything was ready, they were assigned to a seat in the laboratory. First, they were informed about the purpose of the tests and what they involved. Then, they were told about the documents they should fill in: the SAM questionnaire, a social-demographic data sheet, and a consent form that had to be signed, which explained this procedure has been certified by the corresponding ethical committee CEISH-UPV/EHU, BOPV 32 (M10_2016_189) and that all privacy rights were preserved and laws related to these experimental procedures were being respected [39]. After connecting all the electrodes for data collection and before starting to solve the puzzle, the subjects were led to a baseline emotional state with a relaxing video. Shortly after the end of the video, each participant began to solve the puzzle, within a pre-established and known period of time. When time was over, the subjects watched the same video in order to be led back to a baseline level. The last step of the experiment was the emotional evaluation stage.

2.2 Qualitative analysis

In order to analyse appropriately the signals registered in each experiment, the opinion of experts coming from different institutions sited in Spain was gathered: Department of Neurology in the Cruces University Hospital, where a relevant research line is focused on Parkinson diseases [40]; Department of Social Psychology and Behavioral Science Methodology in the University of the Basque Country, with an emotion recognition research line based on physiological analysis [41]; and Department of Developmental and Educational Psychology of the University of Valencia, where complementary studies about dynamic complex problem-solving task are made [42].

The arousal in response to a stressful event is reflected in the physiological signals with an increment in the sweat rate and a decrement in HRV. Therefore, it is necessary to carry out a preliminary study based on the evolution of these signals over time.

An analysis of the GSR and HRV behaviour within the time domain, together with the marks and comments recorded during the experiment, and the answers given by the participants in the questionnaire/interview phase showed different levels of stress inter and intra-subject. As an example, Fig. 3 shows the evolution of HRV and GSR signals from two different subjects, A and B, together with the numbered mark where they experienced the stressful events. Subject A corresponds to Fig. 3(a), and Subject B with Fig. 3(b).

On the time axis, there are three important moments that have been marked: the beginning of the experiment (0 s), the basal end of the first video, that coincides in time with the beginning of the puzzle resolution (123 s), and the end of the pre-established time for resolving it (720 s).

In a first analysis of physiological responses and following the ideas mentioned in the introduction, two important characteristics can be identified.

The first is that the effects of stressors on physiological response depend on the importance of the situational appraisal and the cognitive interpretation of that arousal. This can be observed in the graphs of Fig. 3. At the time the basal video ends and the puzzle resolution phase (M1) begins, subjects feel that the "danger" is significant and their bodies respond with a high level of arousal to face it.

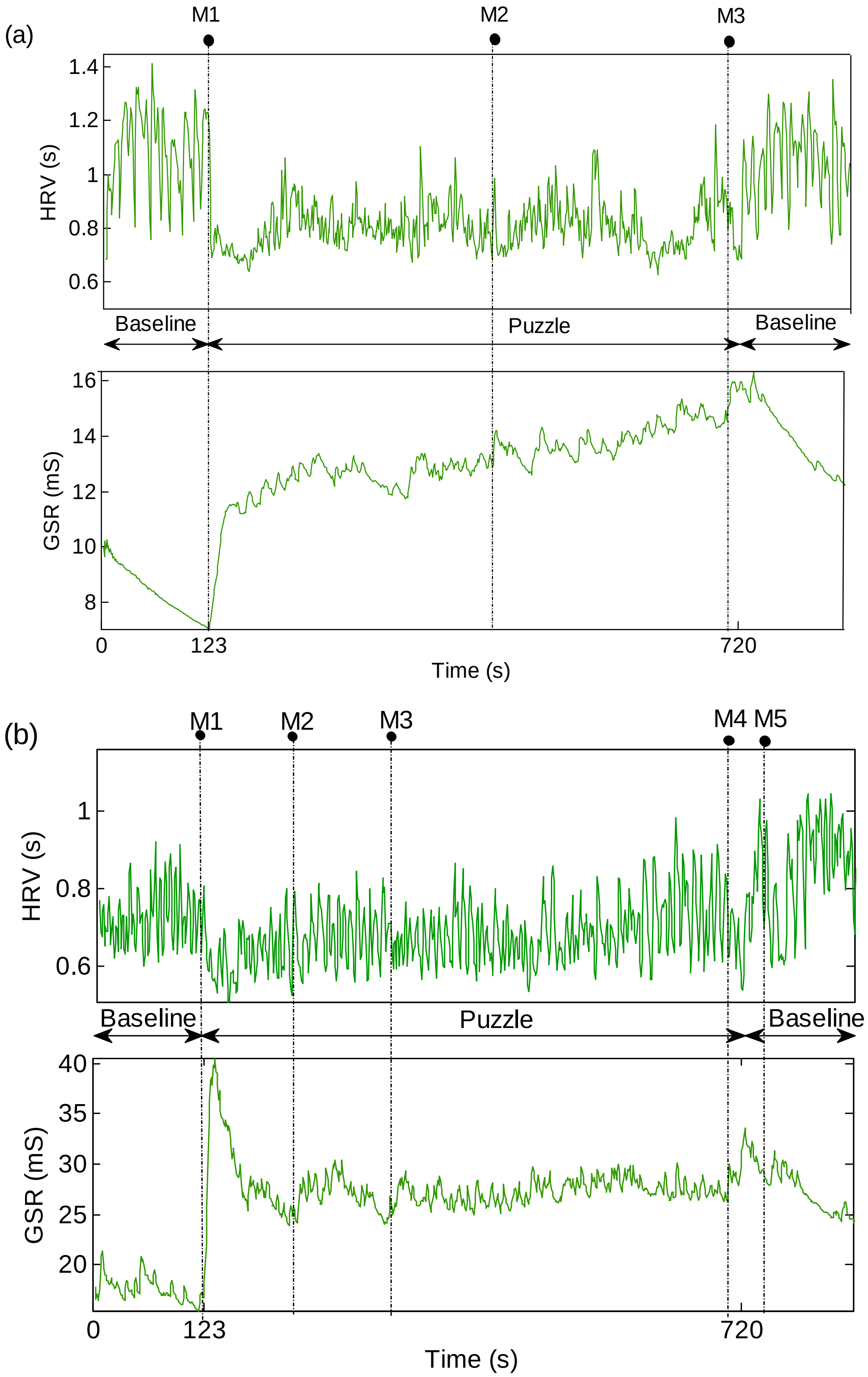


Fig. 3 - The physiological data collected from the HRV and the GSR corresponding to Subjects A and B (figures (a) and (b), respectively).

The response is different when one piece of the puzzle falls (M2 for subject A and M3 for B) when the arousal is lower. It can be seen how at M1 signals change more significantly than at other marks.

The second important aspect to consider is the perception that each subject has of the durability of the danger: it may be a momentary alert or continuous stress. Taking into account the information from the personal interviews after the experiment, it can be said that the subjects A and B, had a different response to facing the start to solving the puzzle (M1).

In the case of Subject A continuous stress occurred and, just at that moment, the HRV lowered and stayed around this value for a few seconds, moreover, the GSR signal increased quickly and did not fall. By contrast, Subject B underwent a 3 momentary alert and therefore their signals changed to cope with this event, but without maintaining the changed levels.

After a thorough analysis of all subjects, considering the accomplishment of the tasks, the marks introduced during the experiment, the emotional evaluation performed through a questionnaire, and analysing the variation of the signal magnitude based on the proposal of Selye [14] and the development made by Kim et al. [15], three degrees of activation were able to be identified: low, medium and high. Moreover, regarding the duration of the changes in the signals based on works as the one of Ursin and Eriksen [16], two behaviours were detected: momentarily generating an alert condition, or continuously producing a stressful situation. This allowed us to focus this work on developing a system that classifies activation in 6 states: “Low Alert (LA)”, “Medium Alert (MA)”, “High Alert (HA)”, “Low Stress (LS)”, “Medium Stress (MS)” and “High Stress (HS)”.

2.3 Quantitative analysis

Following the qualitative analysis in which 6 different states were identified, a quantitative analysis will be presented below. This analysis has been based on processing of the ECG and GSR signals. From the ECG, in order to get the HRV, the intervals between beats were calculated by detecting R peaks (RR), developing several functions in the MATLAB® software platform. In addition, in order to obtain approximations of curves of the HRV and GSR signals a low-pass filter with a cut-off frequency of 0.04 Hz was implemented. We developed an algorithm able to detect, identify, classify and grade the subjects' arousal in real time. To do that, we used 56 out of 166 subjects' compiled data. The remaining 110 subjects have been used to estimate the system performance.

To do the time analysis of the signal in real-time, a sliding window approach has been applied. This technique is often used in the signal processing area [21-24].

It is therefore necessary to define and select the features of the signals to be analysed in each frame or window. Although in research related to emotional behaviour, some analyses are based on the extraction of various statistical, frequency and non-linear features [22,24], our proposal focuses on a single feature extracted from the signals: the value of the slope of them. This decision was adopted because this slope gives information about the speed at which the signal evolves and also whether it increases or decreases, premises that were established and used in the previous qualitative analysis. Moreover, in this work has been possible to establish that slopes analyzed in physiological signals have a direct relation with the "slope concept" introduced by Kim et al. in their quantitative approximation of the GAS model [15].

Once the feature has been determined, the duration or length of the window must be defined according to the temporal needs of the selected feature. Santos et al. used a 10 second window [22], while Healey and Picard selected a 150 second one due to the frequency signal analysis they carried out [24]. In our work we have chosen a 20 second window, less than that proposed by Healy and Picard because no frequency signal analysis is performed, and greater than the one selected by Santos et al. because we wish to recognise the stress level. Besides, since the algorithm is also intended to be able to distinguish between a momentary activation alert and continued stress, it is necessary to study the signal evolution over a longer time period. To do this, the slopes in 3 consecutive windows shifted 5 seconds are analyse. Therefore, to identify a stressful event a minimum of 35 seconds will be required.

The six arousal states defined in the qualitative phase are reflected in this quantitative phase through the study of the HRV slope (sHRV) and GSR slope (sGSR). A continuous analysis of the signals was performed by the shifting window approach and, when nervous system activation is detected, the algorithm recognizes a hypothetical alert with the corresponding arousal level. A stressful situation can only be recognised if this arousal is maintained 15 seconds; otherwise, the event indicates only a momentary alert.

Fig. 4 shows three of the six possible arousal states. It can be seen that Fig. 4(a) shows an insignificant arousal identified with a low alert state, while Fig. 4(b) and Fig. 4(c) undergo greater changes, detecting high alert states. The three following shifting windows in Fig. 4(a) and Fig. 4(b) maintain the arousal and therefore in the last window a stressful state is recognized. By contrast, Fig. 4(c) shows a decrease of the arousal in the second shift, so that a stressful situation is ruled out and the event is labelled as a high alert.

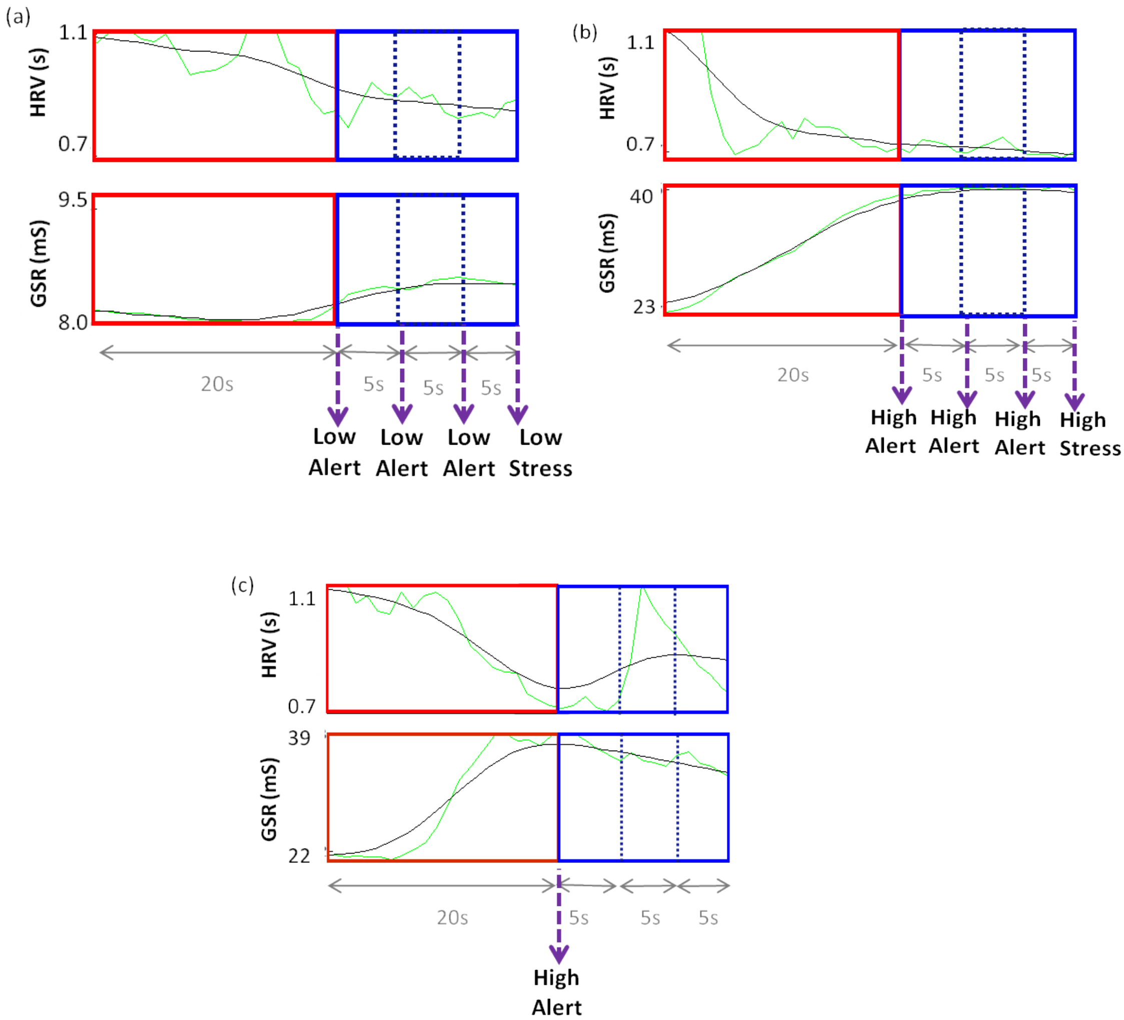


Fig. 4 - Examples of 3 arousal states: (a) belongs to low-stress level, (b) high-stress and (c) high-alert.

To carry out a continuous evaluation of the subject's state in real time, it is necessary to find an automatic detection system. We decided to use a Finite

State Machine based approach since it allows us to determine the behaviour of a system by a program. A set of possible states are defined in which the system can be found, and also a series of transitions between states are defined. These transitions are associated with different events (entries) that are able to appear in the system.

2.4 FSM for automatic detection of arousal states

In an informal description, we can say that a state machine runs sequentially throughout an input sequence. Starting from an initial state, at each step the machine takes one element of the input sequence and changes its state based on the state transition that the input event triggers. This process iterates until it reaches the end of the input sequence [29]. Therefore, the FMS can be defined as following: A=(Q, s, E, q_0, F), where Q is the set of possible states, s is the possible state transition matrix, E is the set of the corresponding conditions for the transitions, q_0 is the initial state and F is the final state.

Based on the identification processes described above, 6 different arousal states are found, and the transitions between the states have been identified. Thus, a FSM has been built with the following parameters: *Q={1-6}* where 1=Low Alert, 2=Low Stress, 3=Medium Alert, 4=Medium Stress, 5=High Alert y 6=High Stress, q_0*={0},* without there being a final state because of its cyclical nature.

Similar to the implementation of functions for signal processing, the software platform MATLAB® has been used for the development of the presented FSM. This FSM is designed to analyse the slopes of the HRV (sHRV) and GSR (sGSR) in a 20-s window with 5-s shift. The transition conditions depend on the thresholds of the slopes of both signals, along with the duration of each arousal episode, evaluated by means of an alert state counter (n) that permits a transition, as shown in Table 1. The particular value of each threshold (Threshold_HRV_1, Threshold_HRV_2, Threshold_HRV_3, Threshold_HRV_4, Threshold_GSR_1, Threshold_GSR_2, Threshold_GSR_3 and Threshold_GSR_4,) is different, but their values remain the same to evaluate all participants. These values have been dimensioned from the classification obtained after the qualitative and quantitative analysis of the signals collected from the 110 preliminary participants (2/3 of the data), carried out by the experts who have collaborated in this work. *E={AR1, AR2, AR3, not(AR1,AR2,AR3), S_AR, not(S_AR), n=3 y Next}*. The AR1, AR2 and AR3 transition conditions occur when the slopes indicate a low, medium and high arousal. As a consequence, the state machine reaches an alert state (1, 3 or 5, respectively). Once any state of alert is reached, if the slopes keep within a small range (S_AR) during at least 3 windows (n=3) the system reaches a stress state (2, 4 or 6, depending on the intensity of the alert state, low, medium or high, respectively). The conditions S_AR and not(S_AR) are used to control the counter and to return to the 0 state when the slopes are not maintained. The Next transition condition is to indicate a non-conditional transition of the state machine.

Table 1 – Conditions and transitions in the FSM.

Transitions	Conditions
Low Arousal (AR1)	(sHRV < - Threshold_HRV$_1$) & (sGSR > Threshold _GSR$_1$)
Medium Arousal (AR2)	(sHRV < - Threshold_HRV$_2$) & (sGSR > Threshold _GSR$_2$)
High Arousal (AR3)	(sHRV < - Threshold_HRV$_3$) & (sGSR > Threshold _GSR$_3$)
Maintained Arousal (S_AR)	(sHRV < - Threshold_HRV$_4$) & (sGSR > Threshold _GSR$_4$)
Next	Mandatory transition
n = 3	If n = 3

Fig. 5 shows the proposed FSM. In order to make the figure clearer the state 0 has been drawn twice, but both states marked with 0 are a unique state, the initial state q_0={0}.

Table 2 presents the matrix of the possible transitions between states. 'From' states are represented by columns, and ''To' states by rows. The symbol '-' means no transition between two states.

Table 2 - Transition matrix for the FSM in Fig. 5.

s	Null	L.A	L.S.	M.A.	M.S.	H.A.	H.S.
Null	Not(AR1,AR2,AR3)	AR1	-	AR2	-	AR3	-
L.A	not(S_AR)	AR1	n=3	AR2	-	AR3	-
L.S.	Next	-	-	AR2	-	AR3	-
M.A.	not(S_AR)	-	-	S_AR	n=3	AR3	-
M.S.	Next	-	-	-	-	AR3	-
H.A.	not(S_AR)	-	-	-	-	S_AR	n=3
H.S.	Next	-	-	-	-	-	-

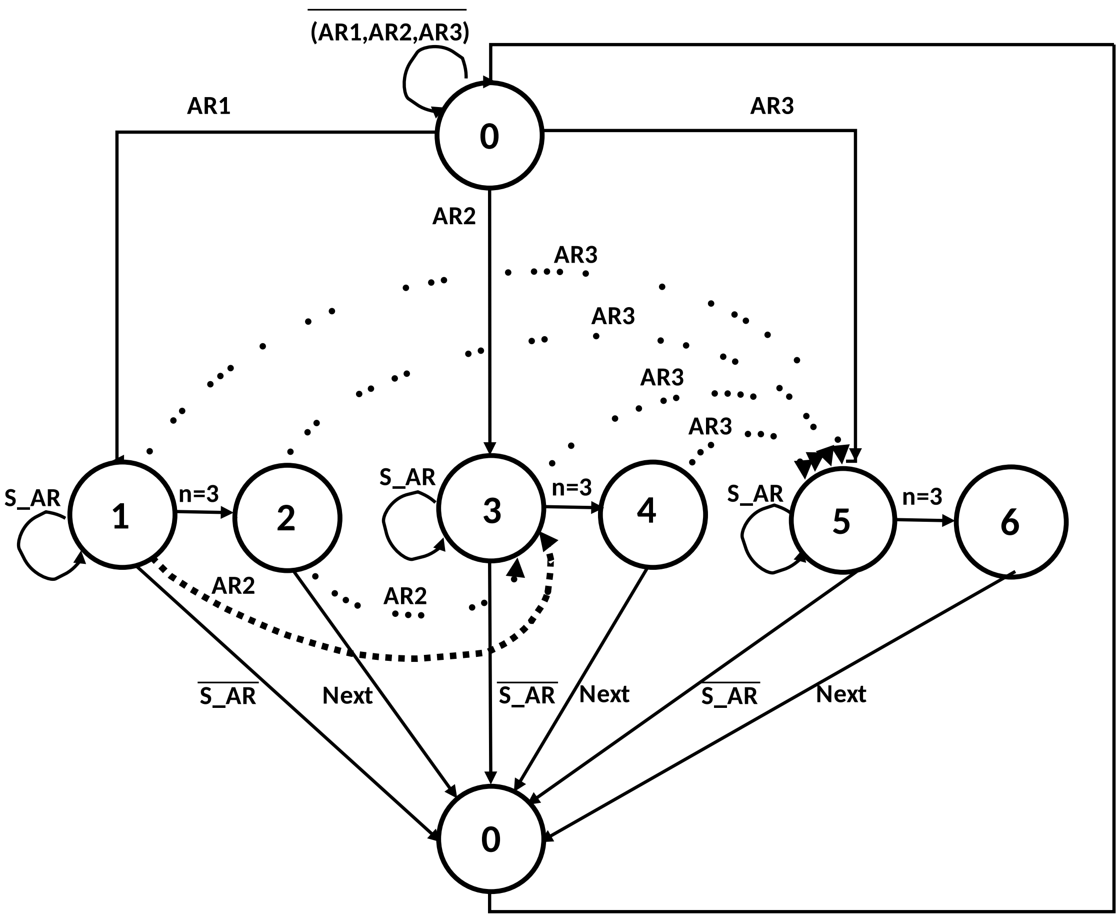
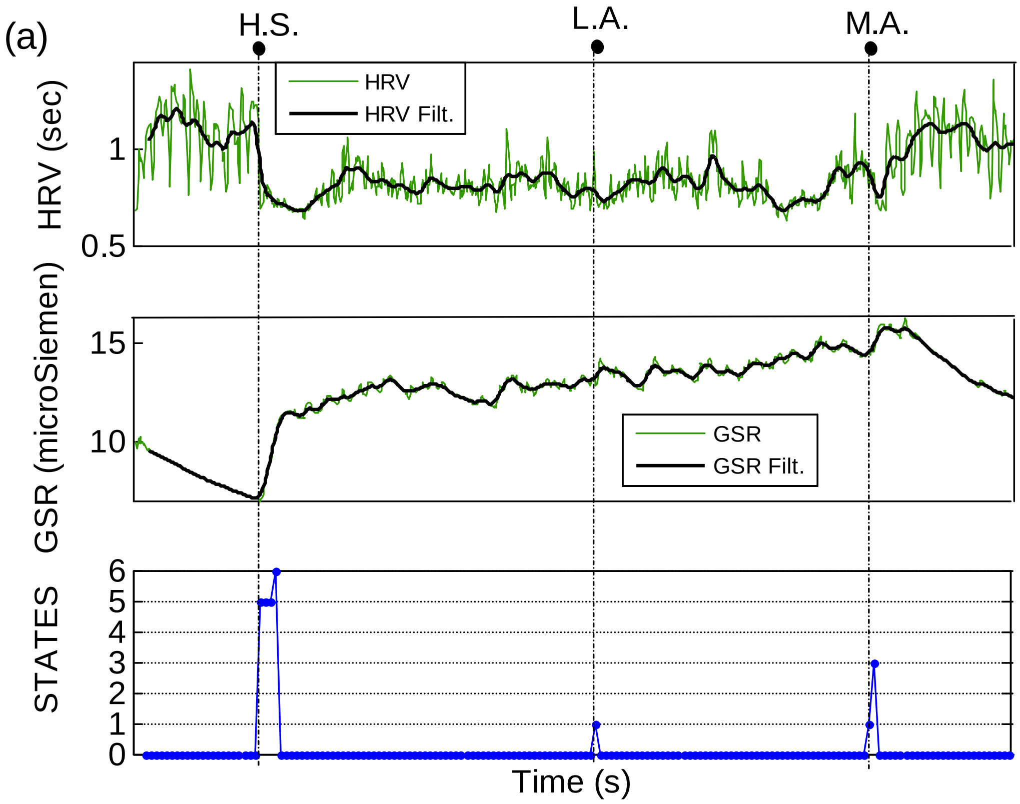


Fig. 5 - Finite State Machine transition diagram for the different alert and stress states.

3. Results

This section presents the performance of the proposed FSM based system to detect the different arousal states in the data obtained from the subjects. All the events automatically detected by the system were compared with the manually introduced marks. Fig. 6 shows three examples with manually introduced marks and events automatically detected by the FSM based system. For all cases, firstly, the original signals (green line) and the filtered ones (black line) are presented for both signals (HRV and GSR); and following these are the states of the system in each moment. The manually marked events are represented by the vertical lines cutting the three temporal diagrams and represent the events that were recorded during the experimental phase with the subjects.



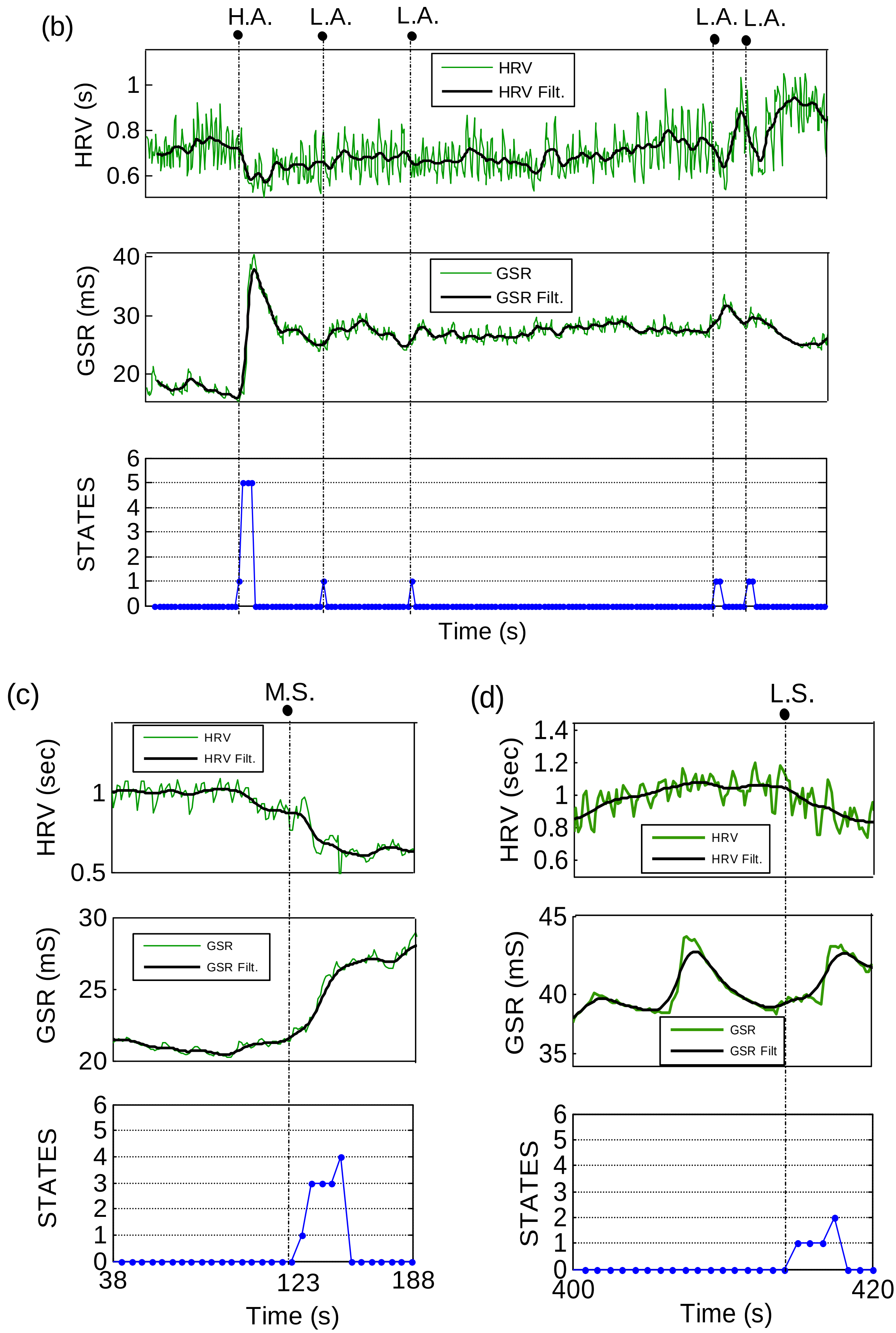


Fig. 6 - Three examples of detection. For each case, HRV signals (upper), GSR signals (middle) and the automatic detection by FSM (lower). On top of each figure the manually classified events are displayed.

The collected data were analysed in order to determine the effectiveness of the FSM. The statistical estimators selected for this purpose were the precision, the recall and the F_1 score [43].

For the calculation of the estimators, it is necessary to obtain: True Positive (TP), the number of states correctly detected by the FSM; False Negative (FN), the number of states that the system should have detected but has not been able to; False Positive (FP), the states classified as positive by the system but without being manually labelled.

Furthermore, F_1 considers both the precision (P) and the recall (R) of the system: P is the number of correct positive results divided by the number of all positive detections made by the system (see equation 1), and *R* is the number of correct positive results divided by the number of positive results that should have been returned (see equation 2). The F_1 score can be interpreted as a weighted average of the precision and recall (see equation 3), it reflects a trade-off between the precision and recall measures and it reaches its best value at 1 and the worst at 0.

$$P = \frac{TP}{TP + FP} \tag{1}$$

$$R = \frac{TP}{TP + FN} \tag{2}$$

$$F_1 = \frac{2 * P * R}{P + R} \tag{3}$$

As showed in Table 3, the results for the high arousal classifications have achieved a precision of 0.974, a recall of 1.000 and F_1 score of 0.987 for high alert, and 1.000, 0.963 and 0.981 for high stress. The precision, recall and F_1 score achieved for medium arousal states are 0.989, 0.968 and 0.978 for medium alert, and 0.923, 0.960 and 0.941 for medium stress. Finally, the results obtained for low level alert and stress states reach a precision of 0.890, a recall of 1.000 and F_1 score of 0.942 for low alerts, and 1.000, 1.000 and 1.000 for low stress.

Table 3 - Results of the FSM system for medium and high arousal states.

	Manual	FSM					
State	Label	TP	FN	FP	Precision	Recall	F_1
High							
High Alert	37	37	0	1	0.974	1.000	0.987
High Stress	27	26	1	0	1.000	0.963	0.981
Total High	64	63	1	1	0.984	0.984	0.984
Medium							
Medium Alert	93	90	3	1	0.989	0.968	0.978
Medium Stress	25	24	1	2	0.923	0.960	0.941
Total Medium	118	114	4	3	0.974	0.966	0.970
Low							
Low Alert	382	382	0	47	0.890	1.000	0.942
Low Stress	13	13	0	0	1.000	1.000	1.000
Total Low	395	395	0	47	0.894	1.000	0.943

Finally, we tried to classify the patterns applying machine learning algorithms. We tested 7 known supervised learning algorithms: Naive Bayes (NB), 1R rule, 1-NN neighbour classifier, Multilayer Perceptron (MLP), Bagging (Bag, combining 10 decision trees), Ada Boost (AdaB, also combining 10 decision trees) and Support Vector Machines (SVM). We use their Weka [44] implementation by applying the default values for their structure and parameters. The input information to the classifiers is the same as that used for the FSM, the slopes extracted from the GSR and HRV signals. We use the same division of the data in order to face the training and validation phases, that is, 2/3 and 1/3 of the collected information, respectively. Table 4 shows the averaged performance achieved with the tested classifiers for discriminating among the defined six classes (alert or stress states, and three activation levels in each state). In all cases, taking into account the F1 score, the best results were slightly worse than the obtained by the FSM (last row in the table).

Table 4 – Averaged performance of the machine learning classifiers.

	Precision	Recall	F_1
NB	0.671	0.322	0.435
1R	0.829	0.851	0.840
1-NN	0.746	0.740	0.743
MLP	0.839	0.869	0.854
Bag	0.937	0.956	0.946
AdaB	0.946	0.962	0.954
SVM	0.854	0.517	0.644
FSM	0.921	0.991	0.955

4. Discussion

In this study, we presented an automatic stress classification system, analysing two physiological signals: Galvanic Skin Response and Electrocardiography. We have selected both signals to achieve a more reliable and robust detection system, as Bakker et al. pointed out in their work [45].

An analysis of the behaviour of GSR and HRV within the time domain, together with the marks and comments recorded during each experiment and the answers given by the participants in the questionnaire/interview phase revealed different levels of stress inter and intra-subject, as can be seen in Figure 6. This is due to the expression of the individual perception that each person has for a particular stressor. These results confirm the hypothesis of Schachter and Singer about behavioural individuality to stress [13].

Therefore a qualitative analysis of the temporal evolution of the signals and stressful events has been carried out in order to identify different states of stress. One of the most significant and innovative proposals of this work is that, besides achieving the identification of stressful episodes, the FSM is able to classify stressful states in different categories. From this analysis, it has been concluded that it is possible to define six activation states: Low Alert, medium alert, high alert, low stress, medium stress, and high stress. The main difference between alert and stress states is the duration of the activation, as mentioned by Ursin and Eriksen [16], being longer for the stress states than for the alert states. The emotional impact caused by the stressor is quantified by the level of the stress (high, medium or low).

In order to design a system able to automatically detect the defined stress states in real time, a Finite State Machine based system was built. The input for the system is a 20-s window with 5-s shift.

It should be noted that the input of the system is an easily calculable feature, the slope, extracted from two signals that were able to be acquired in a non-invasive way. The calculation of such slope is directly related with the proposal of Kim et al. [15].These aspects make the system suitable for real-time detection of stressful states and appropriate for its integration in an end device. Another advantage of this approach is that the solution provided is independent to the individual and the numeric range of the measured signals.

The performance of this system has been evaluated by means of F_1 score, achieving 0.984, 0.970 and 0.943 for high, medium and low arousal states, respectively. A deeper analysis of the FN cases was carried out. The level for the arousal of 4 out of 5 errors was correctly identified. The problem was with the final state: two medium alerts were identified as medium stress states, one medium stress was misidentified as a medium alert, and one high stress case was misidentified as a high alert. The fifth FN error corresponds to a medium alert; the GSR signal rises at the moment the stressor appears, and, although the HRV signal changes, the change occurs outside the analysed time frame. Consequently, the system is not able to identify the event correctly. It could be considered that the FN errors made by the FSM system are a consequence of exceptional aspects in the behaviour of the signals that divert identification to similar states.

In order to compare and validate the results obtained by the FSM, other machine learning techniques have been tested in Weka [44]. Among all cases, the best results appeared in general slightly worse than the obtained by the FSM. However, in view of these preliminary results, we intend to deepen this study by testing more algorithms and tuning their parameters.

Summarizing, the proposed FSM based system is able to automatically classify arousal states into the six different categories. The most critical states, that is, high and medium level states, are successfully detected, as well as the low stress state. The lowest F_1 score is achieved for the least critical states. Specifically the system has found some low alert states to be not manually labelled because either they had been considered irrelevant, or because there were no visible emotional changes.

5. Conclusions

In this paper, a new system able to detect six different stress categories in real-time has been presented. Two different kinds of activations with three different levels are differentiated into a time frame from 20 to 35 seconds. The inputs of the system are the HRV and GSR non-invasive signals. These signals can be collected in people during monitoring tasks, and be processed in a real-time sense, as the system can be previously preconfigured. The system architecture is based on a Finite State Machine composed of seven different states.

The experimental results validate the proposed system, since a satisfactory identification and classification of stress states has been reached. This system is performed by analysing data collected from several volunteers. Due to the satisfactory results obtained, this proposal will be carried out in a more critical collective, such as that of people with disabilities.

Acknowledgments

This work has been performed thanks to the involvement of the Biomedical Group of the Intelligent Control Research Group (GICI) of the Basque Country (UPV/EHU) and to the “Aula de Ingeniería Biomédica Cruces - UPV/EHU”, to which we would like to thank its effort and dedication. The authors like to thank the experts who collaborated on specific parts of this work and the institutions to whom they belong: Dr. Juan Carlos Gómez from the Department of Neurology in the Cruces University Hospital; Dr. Nagore Asla from the Department of Social Psychology and Behavioral Science Methodology in the University of the Basque Country; and Dr. Inmaculada Fajardo from the Department of Developmental and Educational Psychology of the University of Valencia.

This work was funded by the Department of Education, Universities and Research of the Basque Government (ADIAN, grant IT-980-16); by the Ministry of Economy and Competitiveness of the Spanish Government and by the European Regional Development Fund - ERDF (eGovernAbility, grant TIN2014-52665-C2-1-R); and by the Basque Government (grant IT874-13).

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