

ADAPTIVE SCALABLE SVD UNIT FOR FAST PROCESSING OF LARGE LSE PROBLEMS

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-Motivation

- Selecting the Algorithm
- Selecting SVD Method
- Speaking About the Accuracy
- Improving Previous Work
- Results
- HW FPGA Implementation
- Why and How Scalable?
- Conclusion
- Future Work

- Previous Project
 - Computational Intelligence applications
 - Real Time Computation
 - LSE problems
 - Resulting Matrices:
 - Large-scale
 - Rank-deficient
 - Ill-conditioned matrices
 - Implementation in MicroBlaze → Too Much Delay
 - Need for acceleration → parallel processing & optimized faster implementation → FPGA

SELECTING THE ALGORITHM

WHY SVD ?

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- We needed an algorithm numerically robust
- Struggling with deficient matrices
- Struggling with non-square matrices
- Avoid the Inverse calculation
- Obtain the Pseudoinverse
- Good Base for Problem Reduction (future Work)

SELECTING SVD METHOD

WHY ONE-SIDED JACOBI?

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- Easily Parallelizable → **Jacobi**
- What more?
 - Purely non-conflicting → **one-sided**
 - Optimizing the managed unit size → **one-sided**
- Main features
 - Based on Column Pairs Orthogonalization
 - Given's rotations by Rutishauser formulas

$$\tan(2\theta_{ij}^k) = \frac{2 * (A_{:,i}^k * A_{:,j}^k)}{\|A_{:,j}^k\|^2 - \|A_{:,i}^k\|^2} \quad AV = W \quad A = USV^T$$

SPEAKING ABOUT THE ACCURACY IMPOSED CONDITIONS

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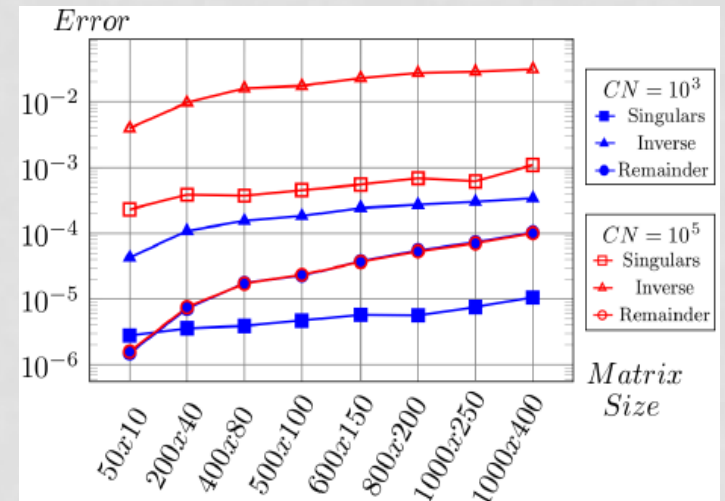
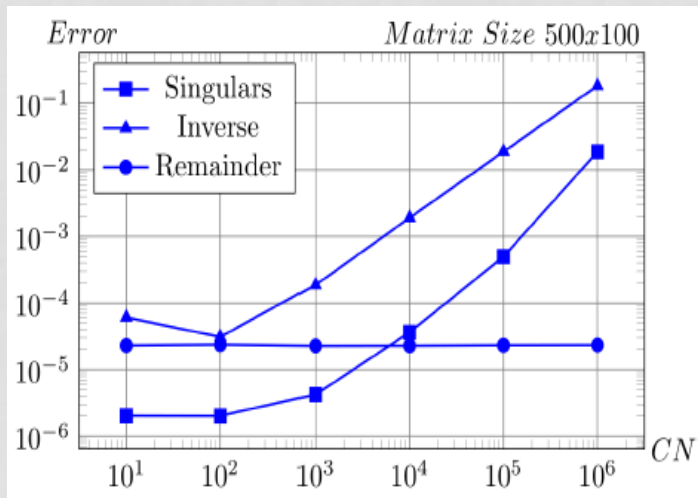
- Computing Precisions → Sets The Maximum
- Matrix Conditioning → Impacts on the Accuracy
 - $K(A) = 10^k$; $CP = 10^m$; Solution = 10^{m-k} .
 - Matrix Size → Posible Accumulated error.
 - $K(A)$ & Matrix Size Impact close to CP → No Solution or very degraded

SPEAKING ABOUT THE ACCURACY: IMPOSED CONDITIONS

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- Randomly generated matrices f(Size, k(A))
- Errors: Our Algorithm ('') in Single Vs Matlab('') in double

- Singulars = Maximum Normalized Error = $\frac{\sigma' - \sigma''}{\sigma''}$
- Inverse = $\|A'_{inv} - A''_{inv}\|^2$
- Remainder = $\|A - SVD\|^2$

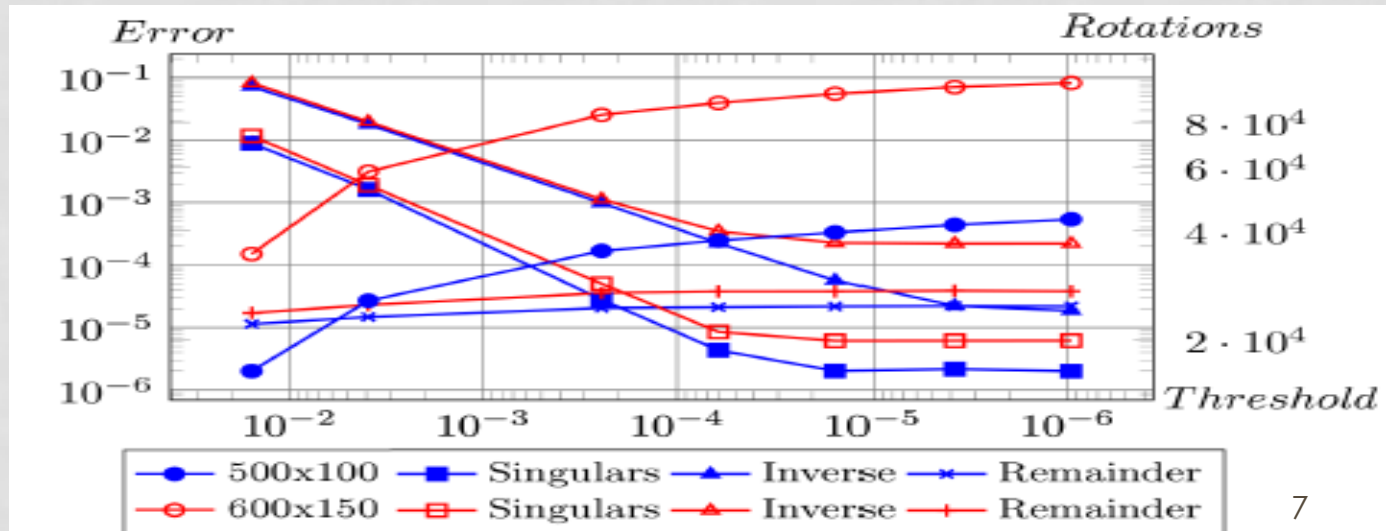


SPEAKING ABOUT THE ACCURACY DECIDED CONDITIONS

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• Threshold Value

- Iterative Algorithm Finisher → Orthogonalization
- User Defined Parameter → Time & Accuracy Trade-off
- Error Saturation Phenomenon → (Imposed Conditions)



IMPROVING PREVIOUS WORK LEARNING FROM OTHERS

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- **Brent and Luck**

- Highlighted the column norm importance
- Normalized the Threshold → Adapting to the columns' norm → Actually calculating the cosine: $\frac{A_i \cdot A_j^T}{\|A_i\| \|A_j\|} < Threshold$

- **Hestenes**

- Swap the columns → Active Sorting → f(column norm)

IMPROVING PREVIOUS WORK ADDING OUR TOUCH

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- Increased Adaptability
 - Realizing that the “Inverse Error” lies on small columns
 - Being Fussier with them → Harder Threshold
 - With Easier Threshold → Same Solution Accuracy
 - Not rotating in vain the big columns
 - AMN:
 - $\frac{A_i \cdot A_j^T}{\|A_i\| \|A_j\|} = \cos(A_i, A_j) < Threshold \cdot \min(\|A_i\|, \|A_j\|)$
 - AAMN:
 - $\frac{A_i \cdot A_j^T}{\|A_i\| \|A_j\|} = \cos(A_i, A_j) < Threshold \cdot \|A_j\|$

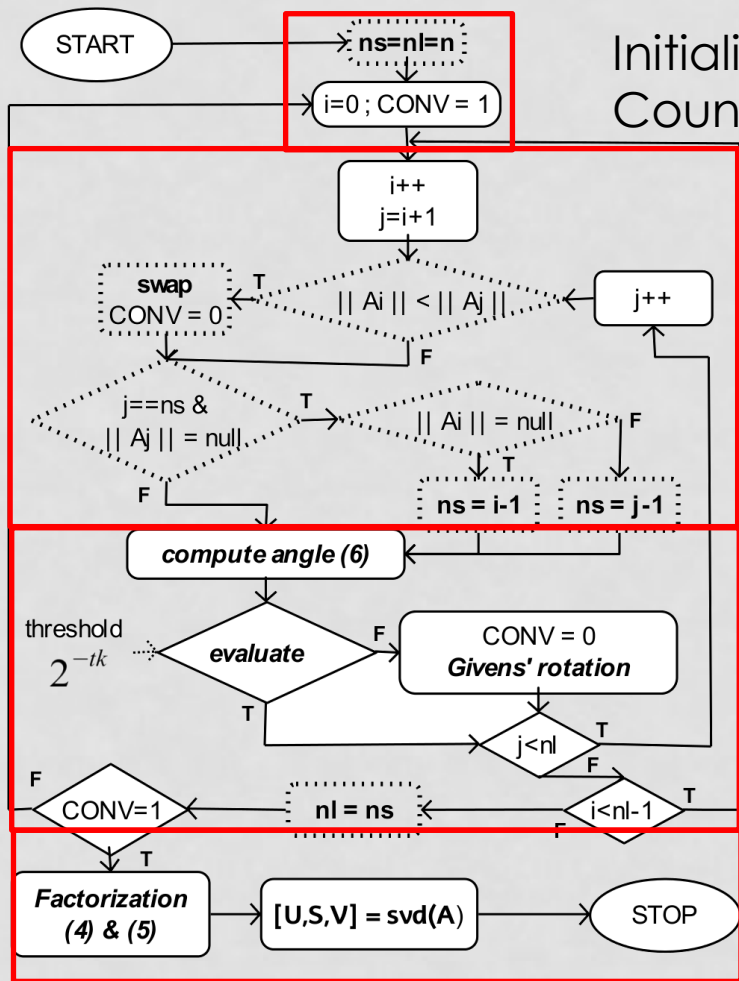
IMPROVING PREVIOUS WORK BEING HW FRIENDLY

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- Initially Two Angles Calculation:
 - The Decision \rightarrow f(cosine)
 - The Rotation \rightarrow f(Rutishauser)
- Cos & Rutishauser \rightarrow both f(columns and its norms)
- Killing two bird with one stone
Decision and rotation \rightarrow f(Rutishauser)
- Readaptation \rightarrow More sensitive
- AARH: $\theta_{ij} < Threshold \cdot \|A_j\|^2$
- Avoiding root squares

THE MODIFIED ONE-SIDED JACOBI

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Initialization: Problem Size, Flag & Counters

Iteration : Swap & Null Columns Management

Iteration : Decision, Rotation & Actualization

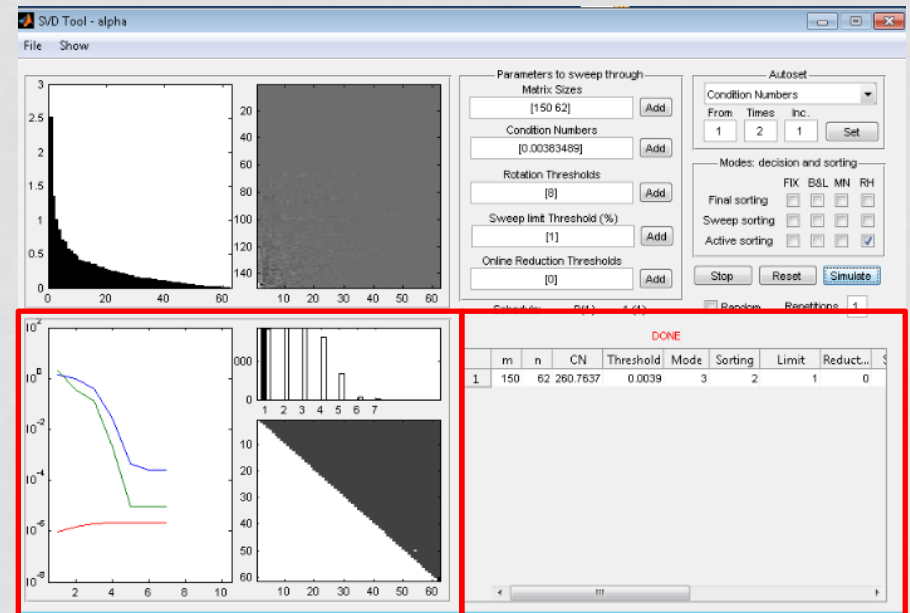
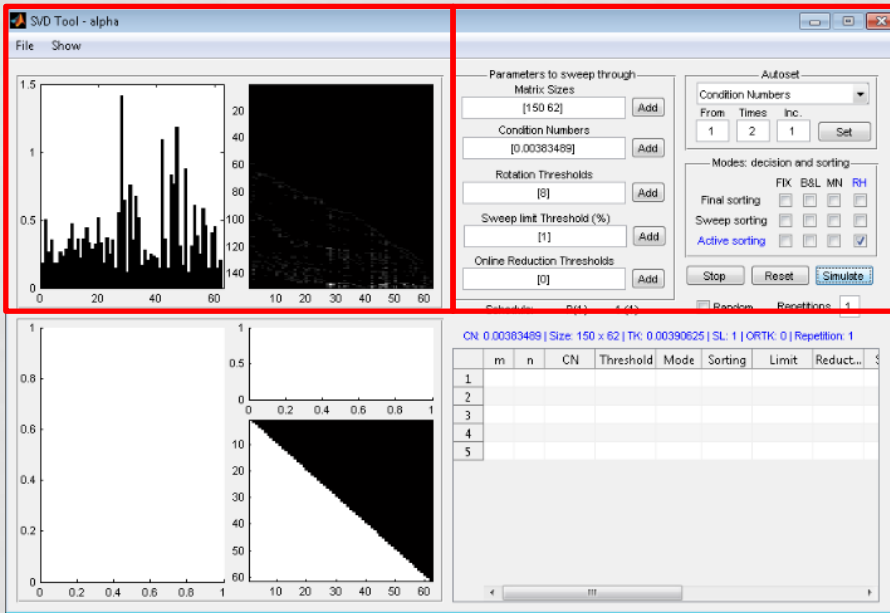
Finish: Matrix Factorization

$$\sigma_i = \|W_{(:,i)}\| \quad U_{(:,i)} = \frac{W_{(:,i)}}{\sigma_i}$$

COMPARATION ANALYSIS TOOLBOX

Column Arrangement

Selection of the Comparison



Error Evolution

Results

RESULTS

COMPARING WITH THE REST

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TABLE I: Comparative of algorithm performance

	Inverse Error Threshold			
Fixed	4.19E-6 24	2.11E-5 24	2.54E-4 24	1.89E-3 24
B&L	3.98E-6 22	1.93E-5 18	1.62E-4 16	1.87E-5 16
ABL	3.68E-6 22	1.83E-5 18	1.63E-4 16	1.78E-3 12
AAMN	5.60E-6 20	1.76E-5 16	1.68E-4 10	1.34E-3 8
AARH	6.77E-6 20	1.87E-5 16	1.76E-4 10	1.41E-3 8
$\kappa(A)$	1,00E+01	1,00E+02	1,00E+03	1,00E+04
Fixed	33,696 11.3	33,530 10.50	33,905 10.50	34,004 10.75
B&L	32,303 9.70	30,911 10.20	29,858 10.15	26,482 10.13
ABL	26,096 8.20	24,356 8.00	23,121 8.05	19,927 7.73
AAMN	25,275 8.13	23,209 8.05	18,353 8.05	15,327 8.30
AARH	25,512 8.40	23,345 8.50	18,960 8.53	16,078 8.35
	Rotations Sweeps			



Obtaining Same Accuracy
→ Easier Threshold

Obtaining Same Accuracy
→ Less Rotations

Obtaining a Better Result
→ The Higher the $\kappa(A)$

TABLE II
TEST MATRICES RESULTS

	Inverse Error $2^{-Threshold}$; Rotations Sweeps		
Size κ	201 × 47 7.5E1	235 × 216 1.7E3	200 × 200 2.4E3
Name	JGD_Kocay/Trec9	JGD_Forest/TF11	Bai/bwm200
ABL	1.99E6 22 5,004 7	1.4E-3 12 97,281 9	2.96E4 14 95,902 9
AAMN	1.96E-6 18 4,903 8	5.3E4 6 75,433 9	1.43E4 8 61,981 9
AARH	2.21E6 16 4,908 9	8.03E-4 4 76,854 9	5.64E-4 6 57,675 10

Testing With Real Matrices & Obtaining Expected Results

RESULTS

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- Savings in Number of Rotations

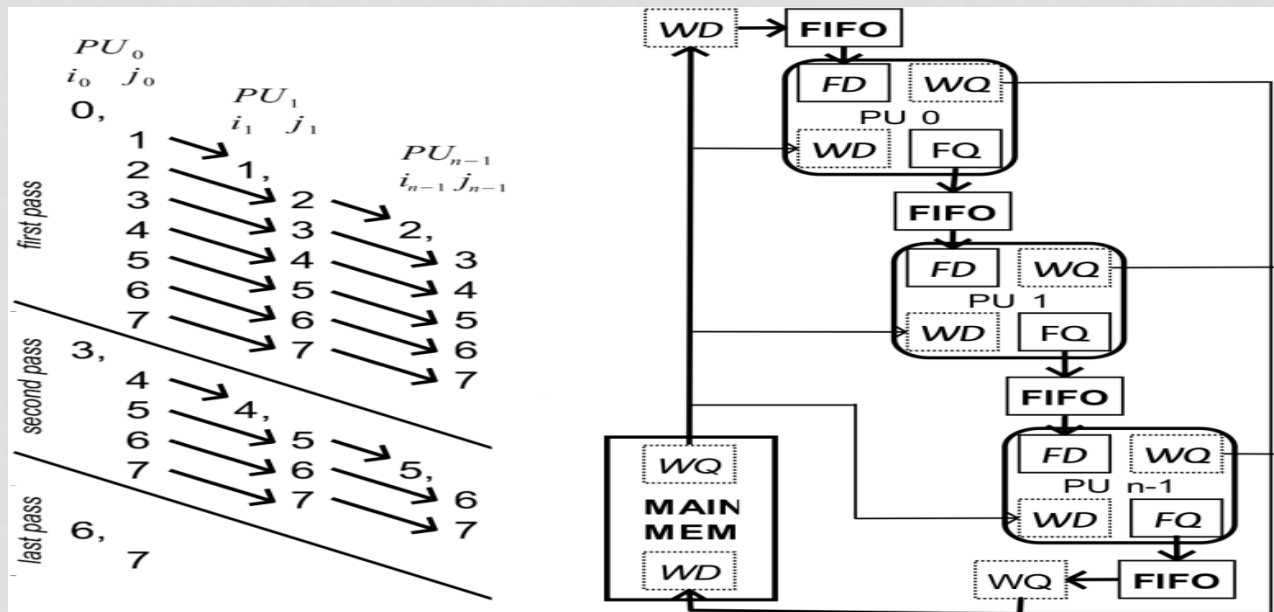
CN	Fixed to AARH	B&L to AARH	ABL to AARH
1,00E+01	24,29%	21,02%	2,24%
1,00E+02	30,38%	24,48%	4,15%
1,00E+03	44,08%	36,50%	18,00%
1,00E+04	52,72%	39,29%	19,32%

HW FPGA IMPLEMENTATION ARCHITECTURE

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Double Data-Flow:

- Primary: Linear array to manage A_i/A_j
- Secondary: Asynchronous full-duplex shared bus to manage V_i/V_j
- FIFO between PUs

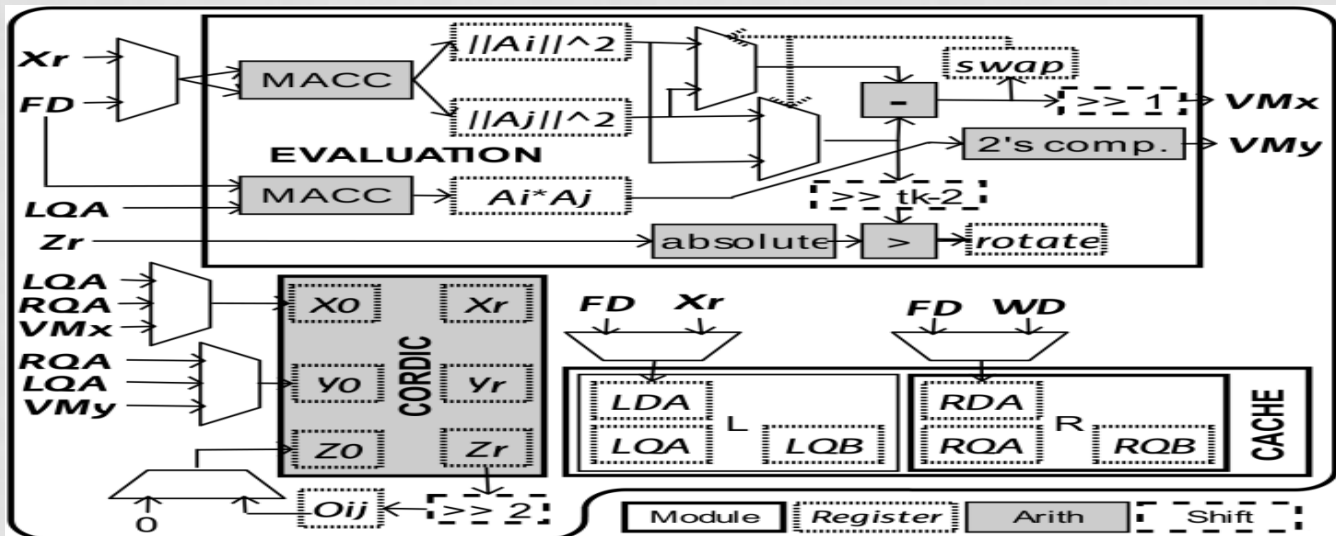


HW FPGA IMPLEMENTATION PROCESSING UNIT

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PU Design:

- Evaluation: Computing square Euclidean norms and vector multiplication, swaping and deciding
- Cordic: Theta calculation and rotations' performing
- Cache: $L(m+n)$ and $R(\max(m,2n))$



WHY AND HOW SCALABLE?

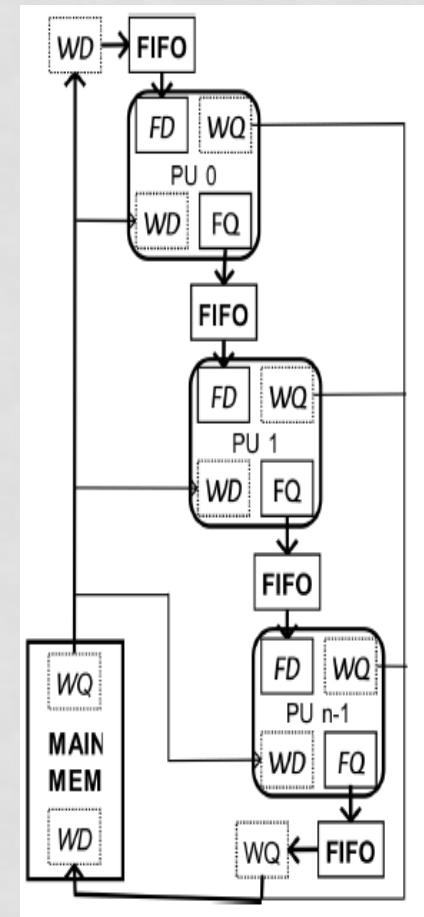
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- No limited to specific matrices and HW: Generic Solution

- Different sizes
- Different Shapes
- Different budgets

- Architecture

- Based on basics processing units PUs
- PUs variable on quantity
- From 2 to $n/2$



IMPLEMENTATION RESULTS

	xc6slx45-3fgg484	xc7k160t-3fbg484
Area	56 %	86 %
DSPs	93 %	60 %
RAM	62 %	44 %
Matrix Size ; K(A)	300x100 ; 10^2	750 x 250
PU	9	60
Frequency	55 MHz	90 MHz
Processing Time	60 ms (5-6 sweeps, 8-16 ms/sweep)	

Word-Length :18 bits

CONCLUSION

- AAMN and AARH proposed outperforming previous proposals.
 - Small Columns Important Columns
 - Same Accuracy Less Rotations
 - User-defined Accuracy -> Threshold
 - HW Friendly
- An implemented parallel processing scheme proposed:
 - Linear Array of PUs
 - Scalable
 - Double Data-Flow

FUTURE WORK

- Online reduction of problem size
- Improve sorting
- Optimize PU design
 - Improved CORDIC realization (Redundant arithmetic (Ercegovac) or Square root and division free (Gotze))
 - Ad-hoc online estimators
 - Atan
 - Square norm

THANK YOU VERY MUCH

- Questions or Details ?