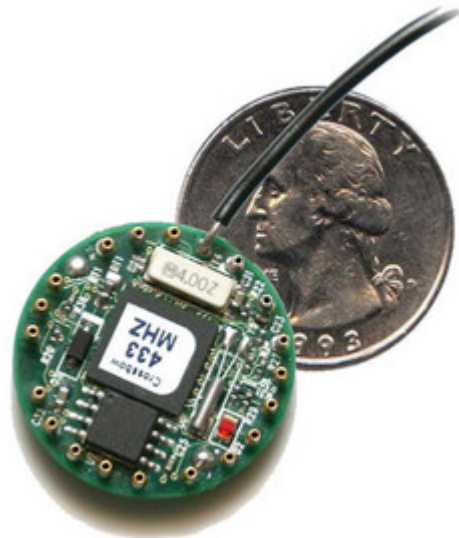


Blocks: Redesigning Coarse Grained Reconfigurable Architectures for Energy Efficiency

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L.J.W. Waeijen
H. Corporaal

Mobile devices



Mobile devices

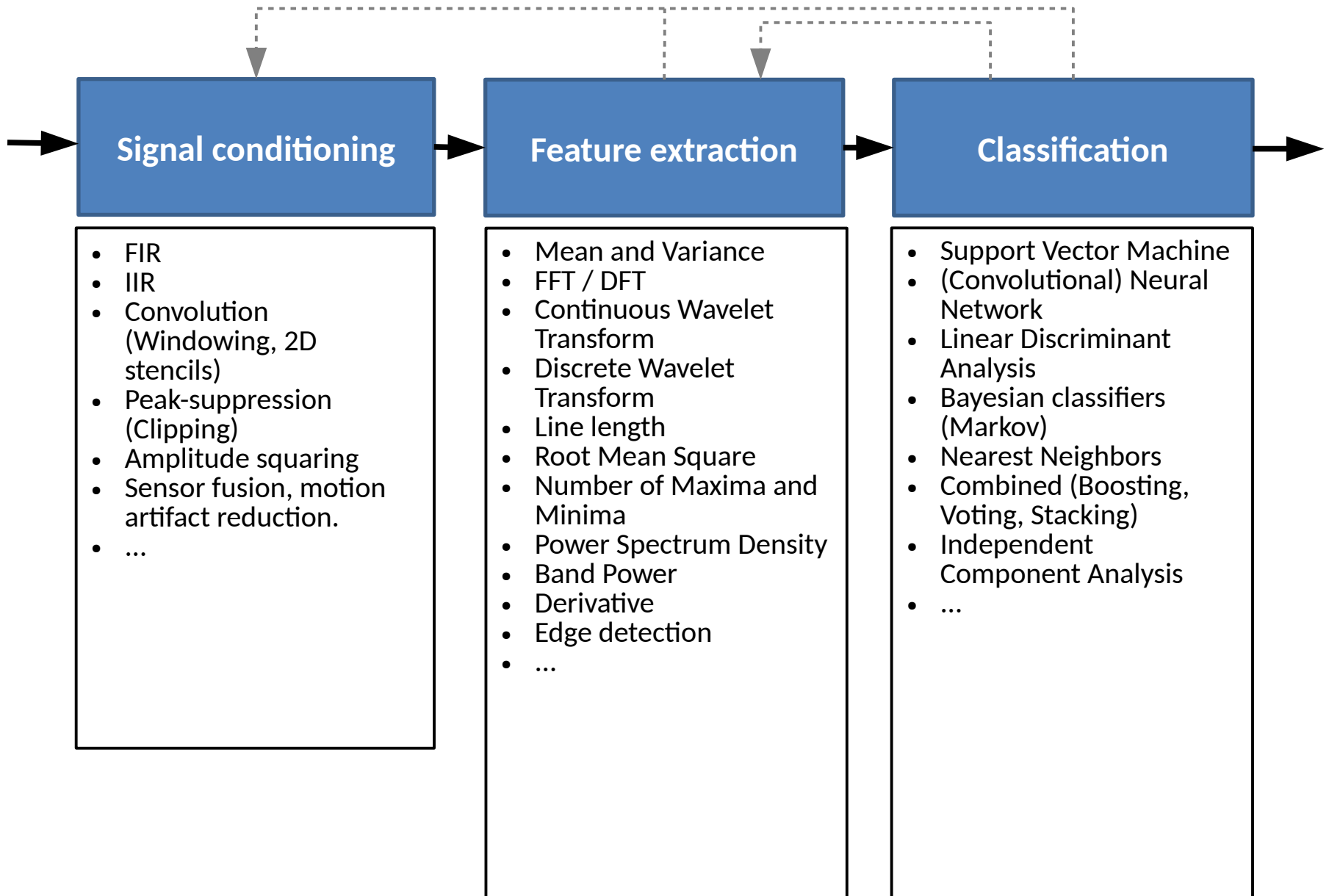
- Limited size
- Wireless communication
- On-board processing



Algorithms

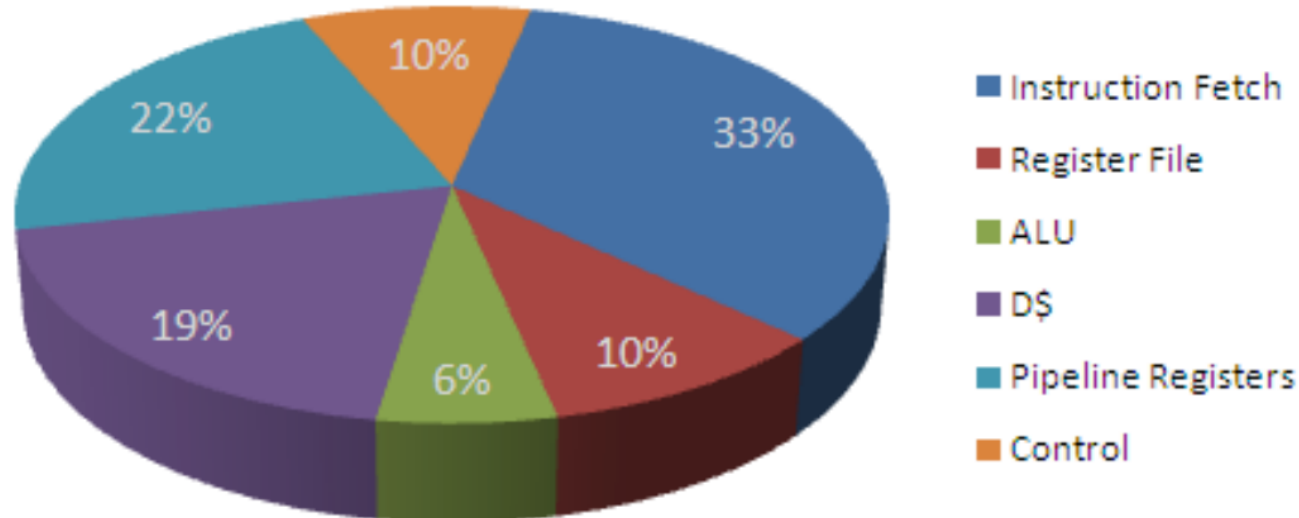
- Wearable medical devices as an example.
 - Low latency can be important.
 - Often significant compute effort.
 - Updates on a regular basis.
 - This rules out an dedicated ASIC.

Algorithms



Popular architectures

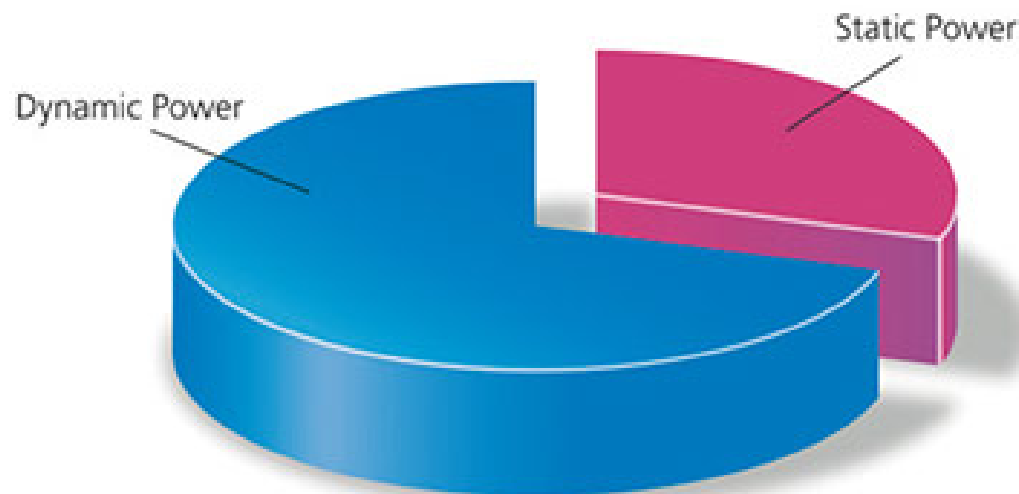
- Microprocessor
 - Quite flexible
 - Reasonable performance
 - Low energy efficiency



[figure: Understanding sources of inefficiency in General-Purpose Chips, Hameed et al.]

Popular architectures

- FPGA
 - Very flexible
 - Good performance
 - Medium energy efficiency

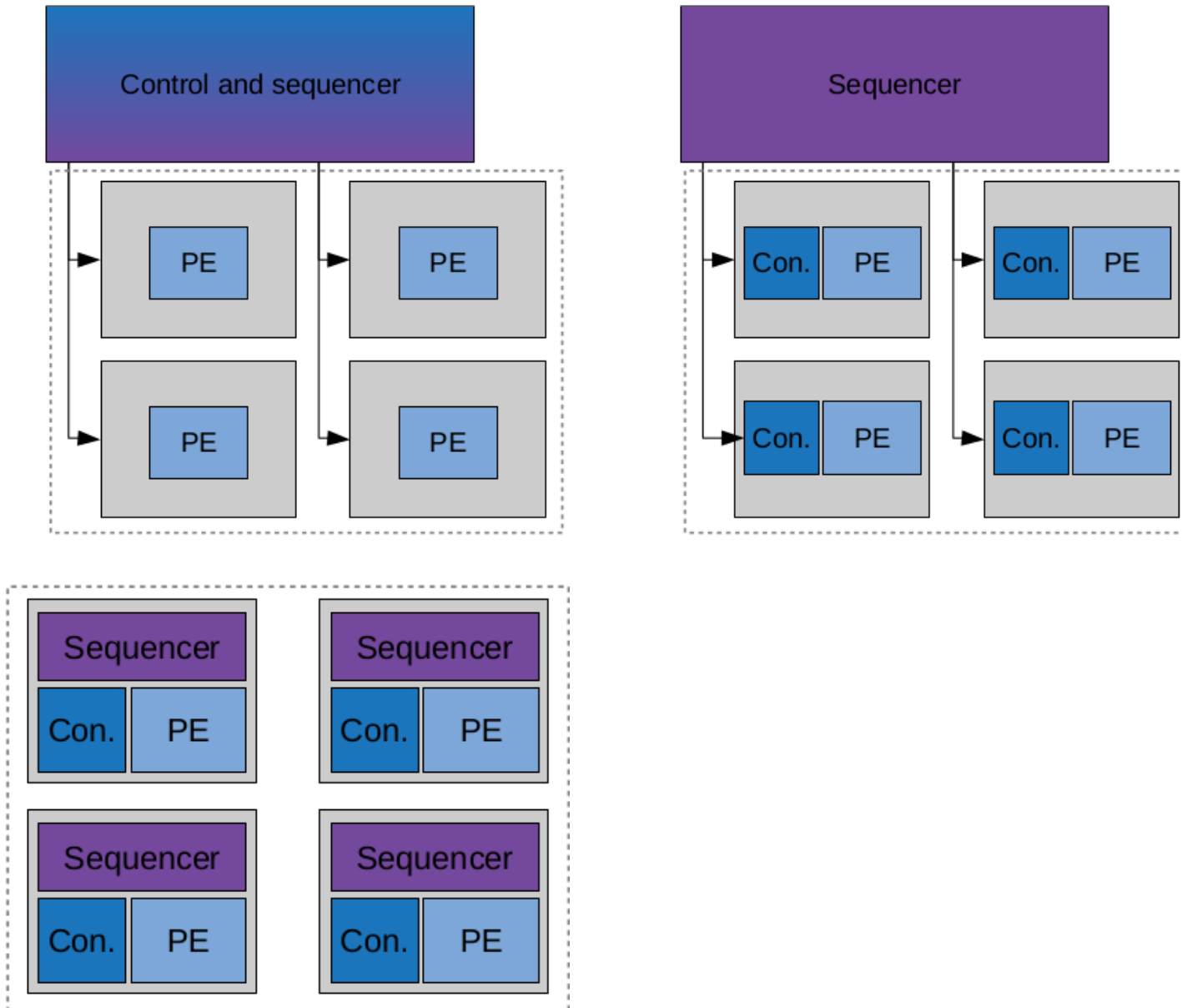


[Figure: ACTEL]

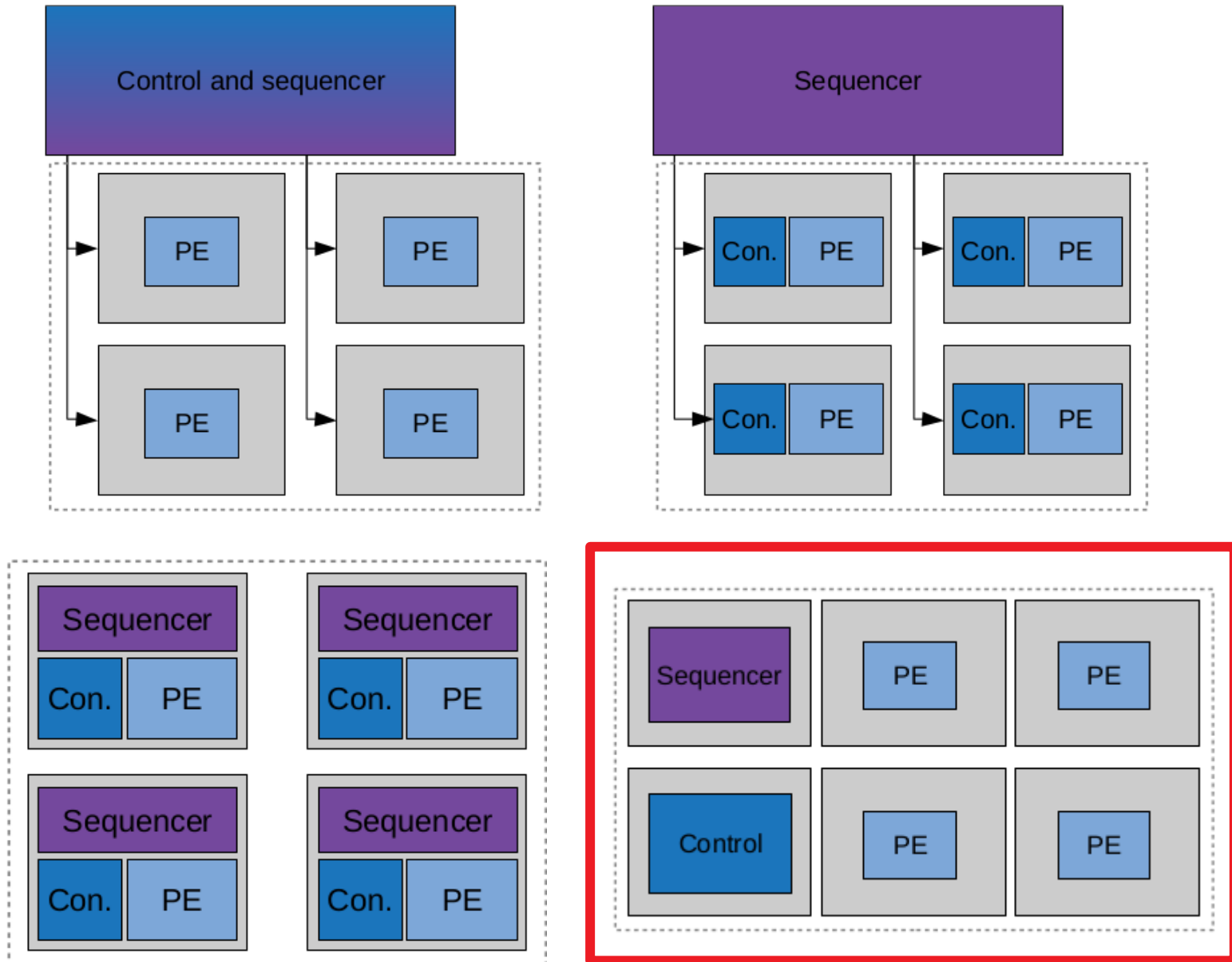
Coarse Grained Reconfigurable Architectures

- Many DSP algorithms do not require bit-level operations.
- CGRAs operate on wider data elements than FPGAs.
- Both spatial and temporal reconfiguration.
- Better energy efficiency possible.

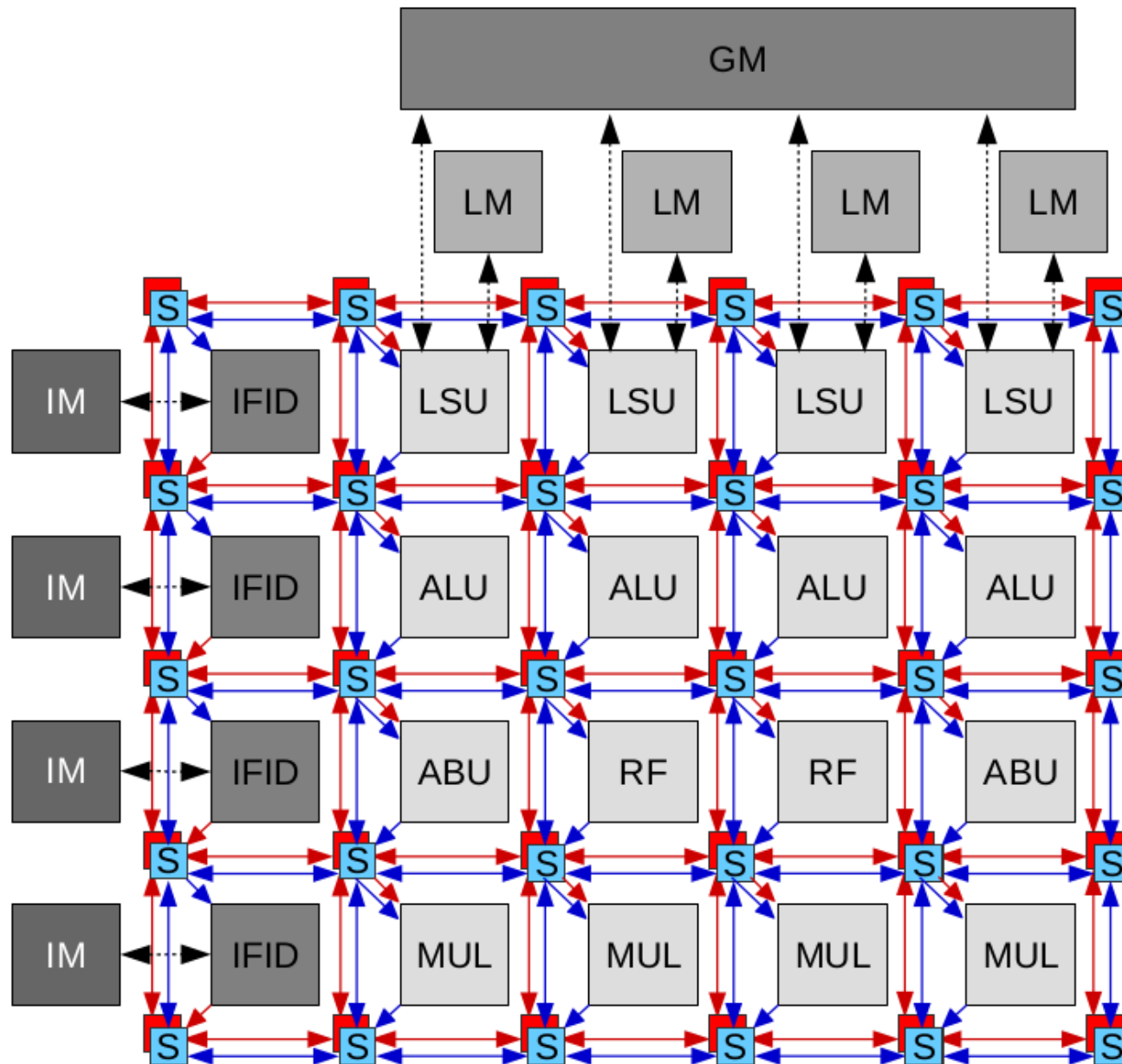
Temporal reconfiguration



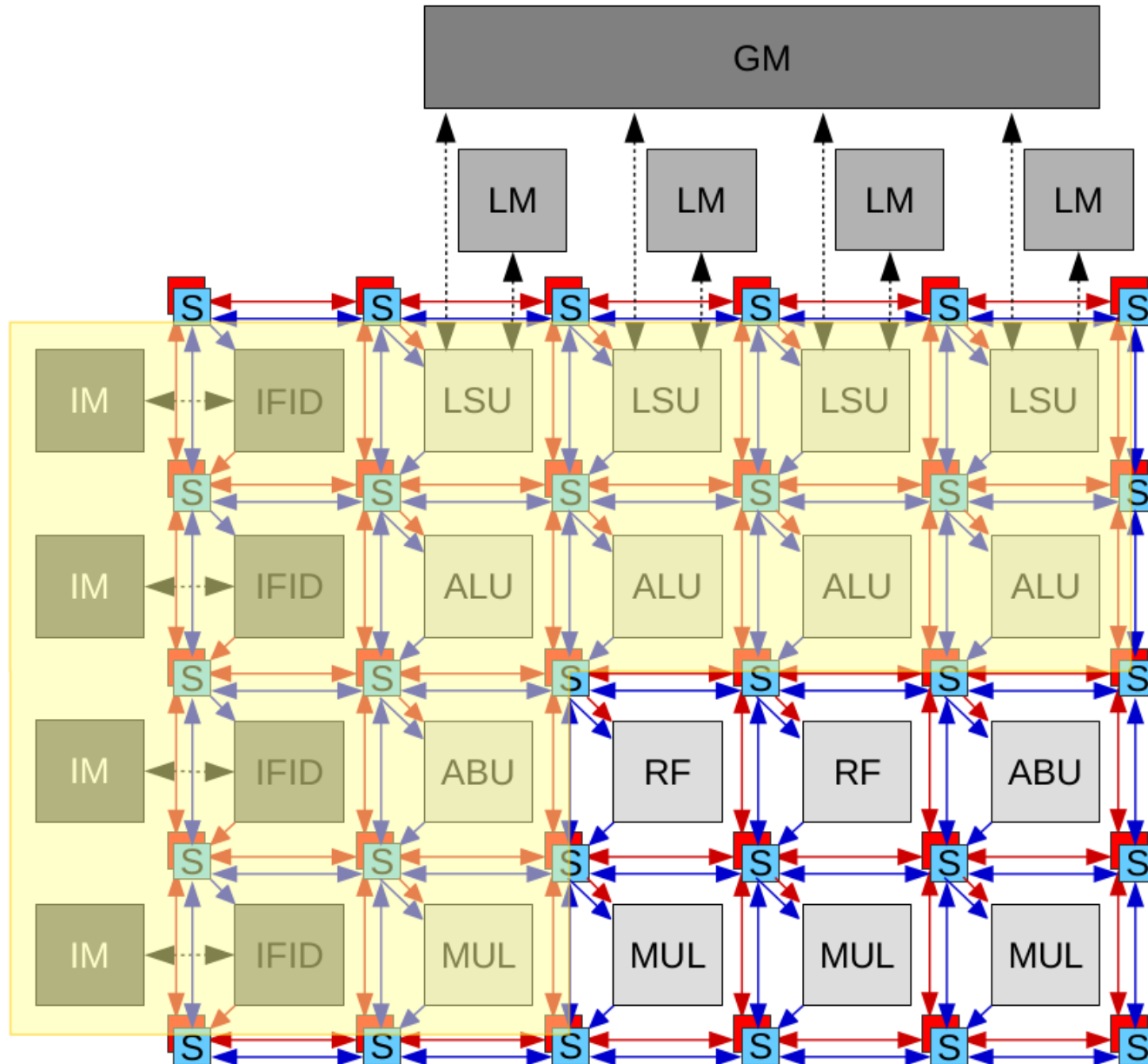
Temporal reconfiguration



Spatial reconfiguration



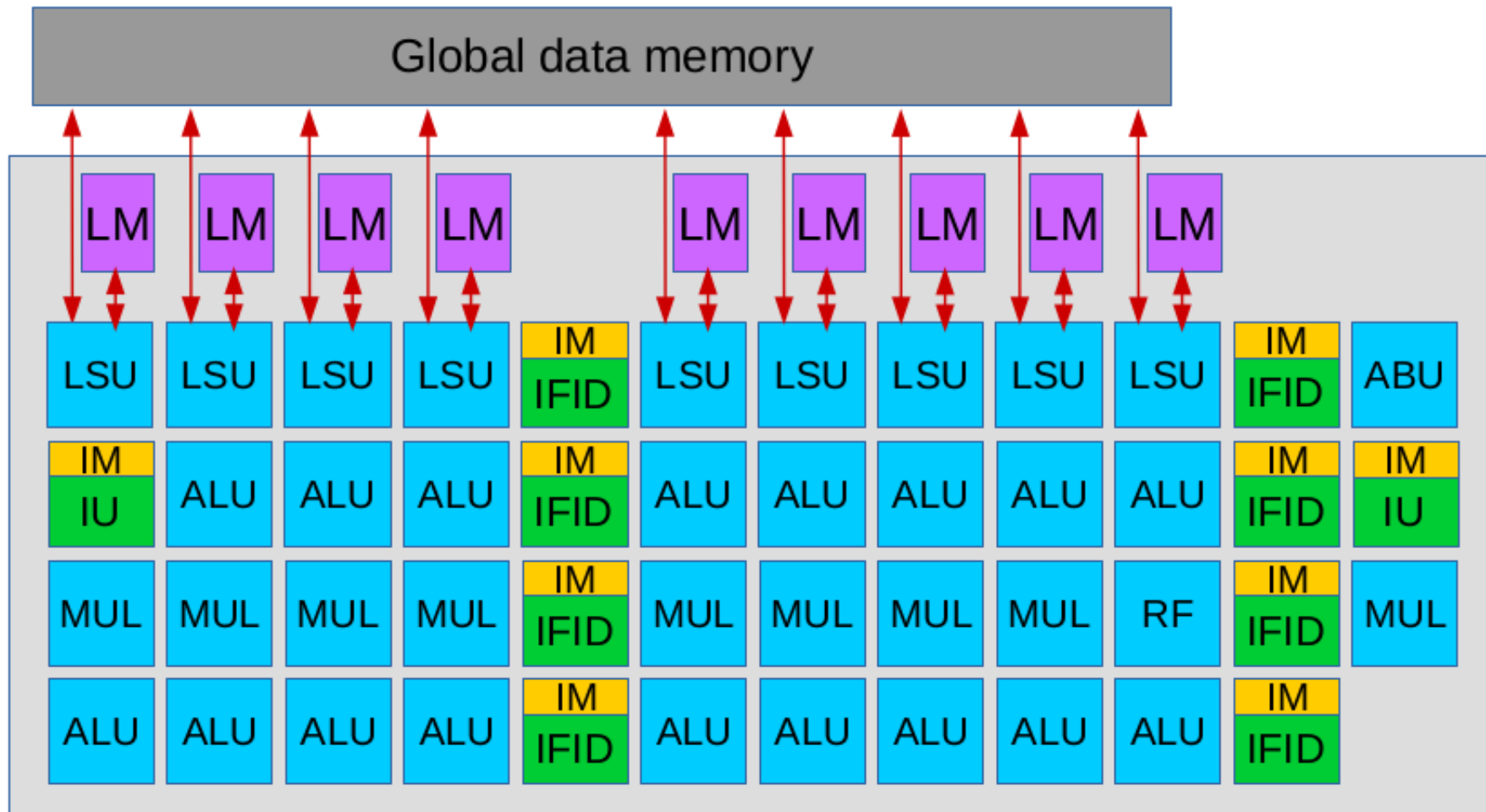
Spatial reconfiguration



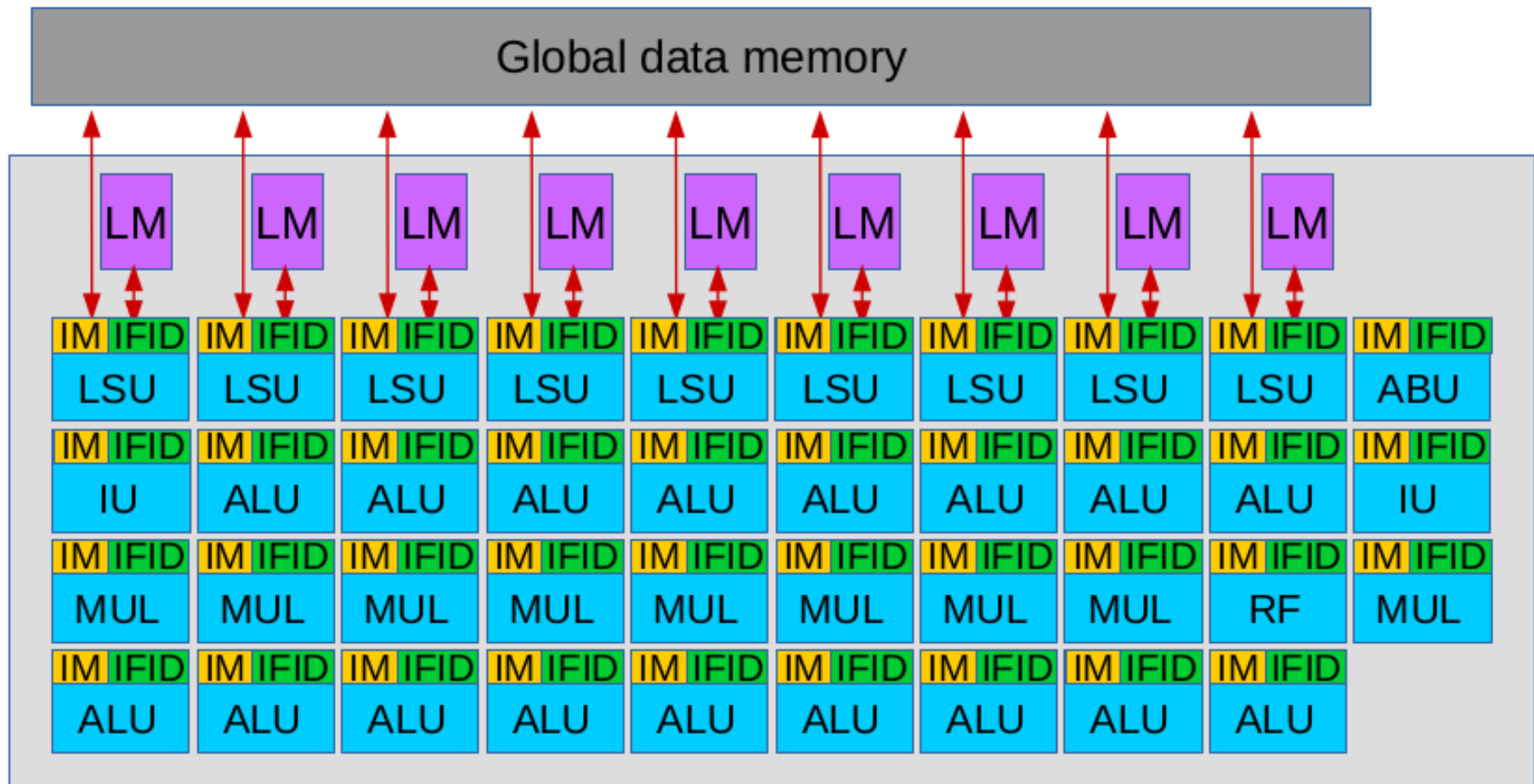
Evaluation

- Numbers obtained with post place-and-route simulation and power estimation on commercial 40nm, low-power.
- Memories included (TSMC)
- For three architectures:
 - Blocks
 - Traditional CGRA
 - Application specific processor
- Eight benchmark kernels

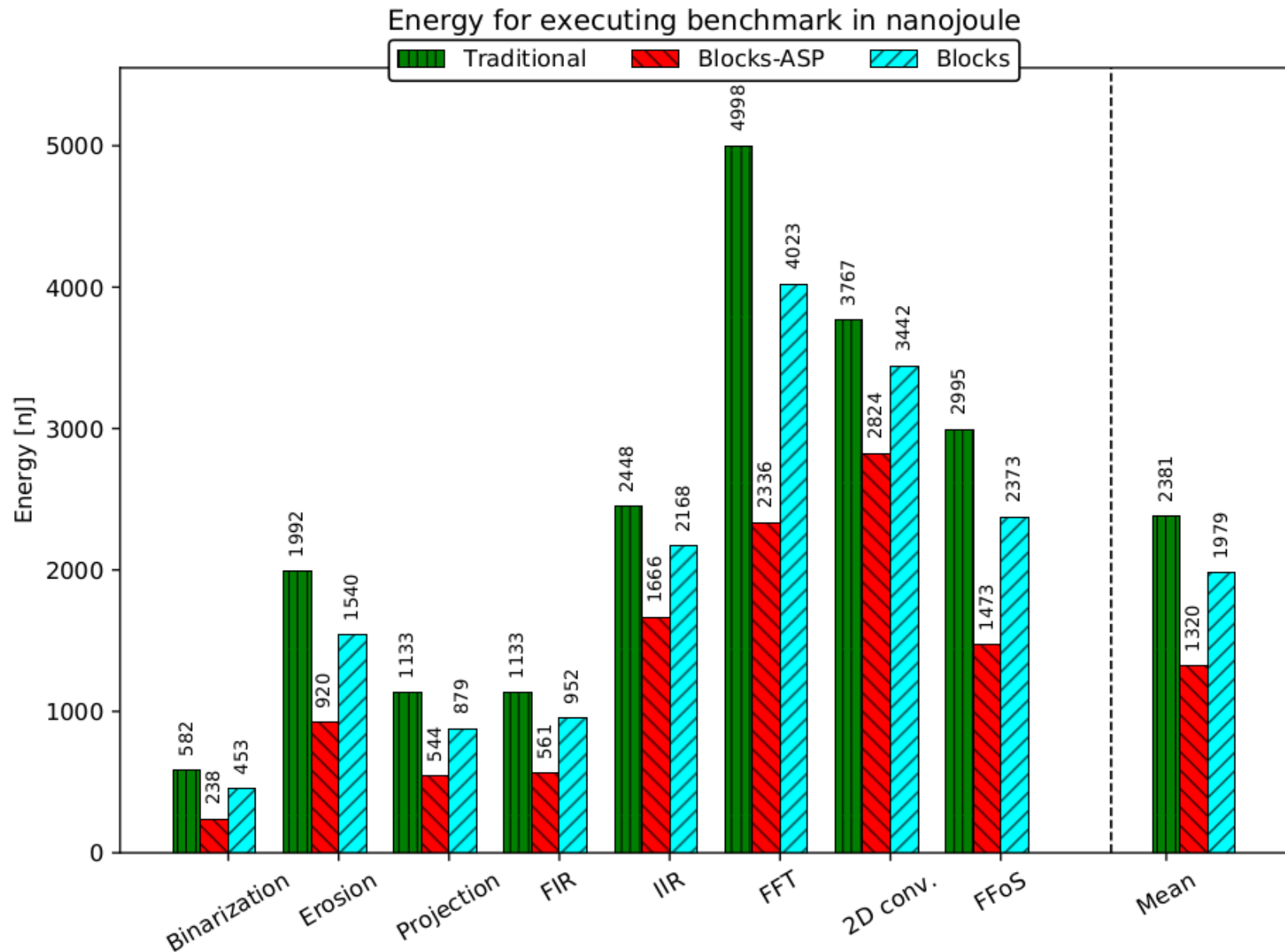
Reconfigurable architectures



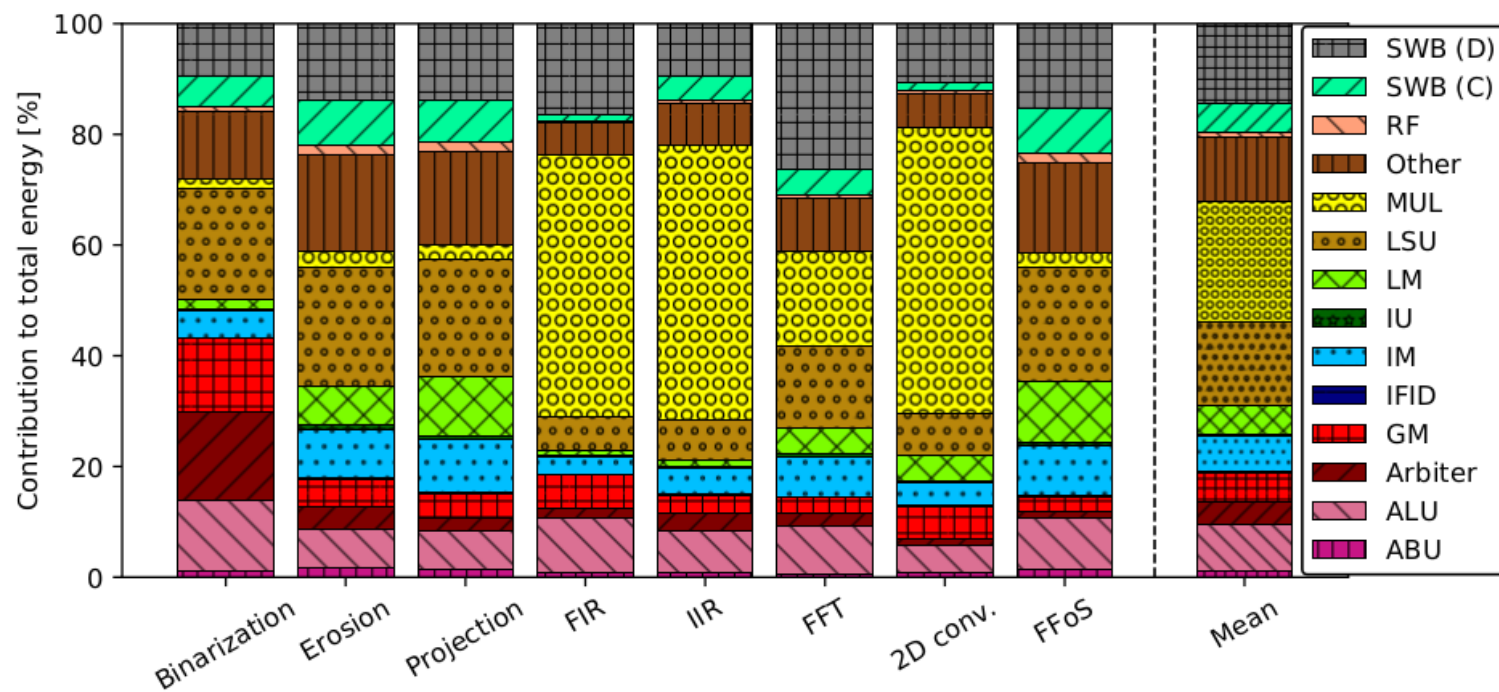
Reconfigurable architectures



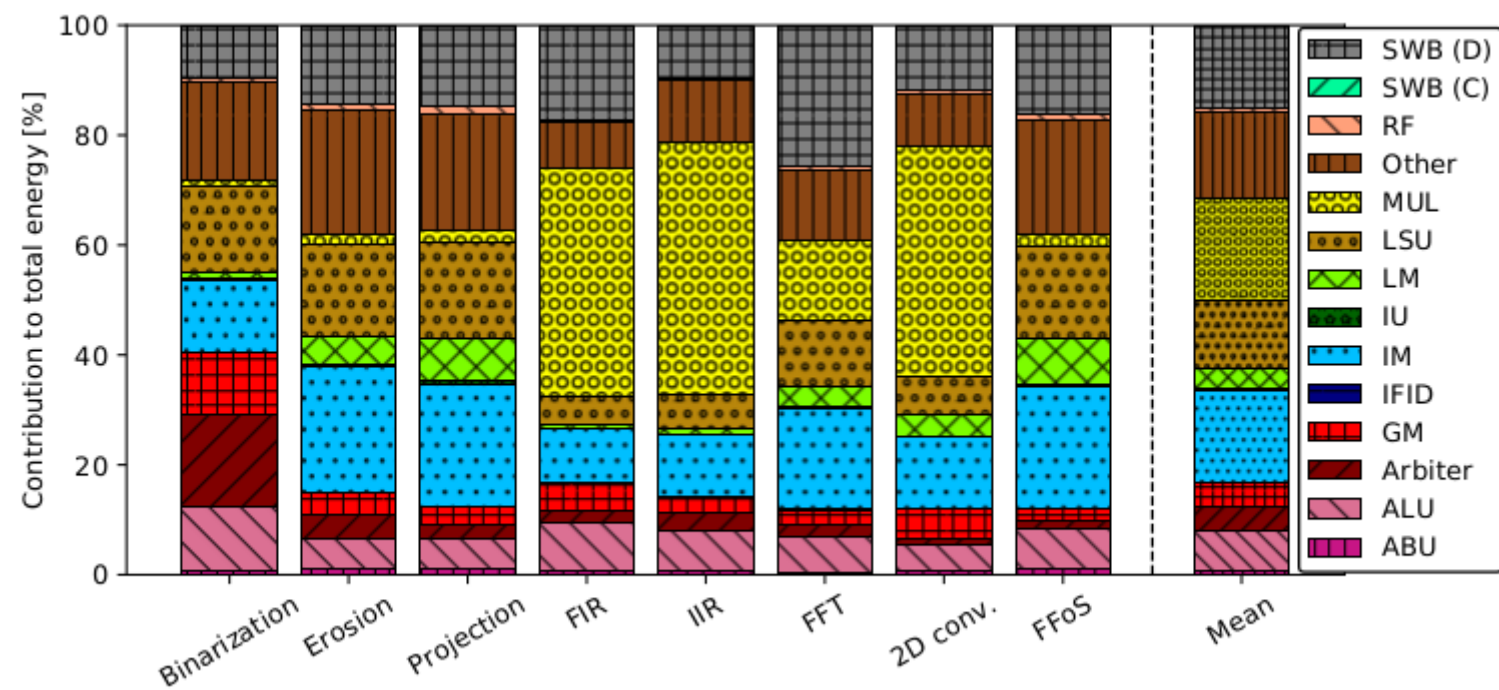
Results



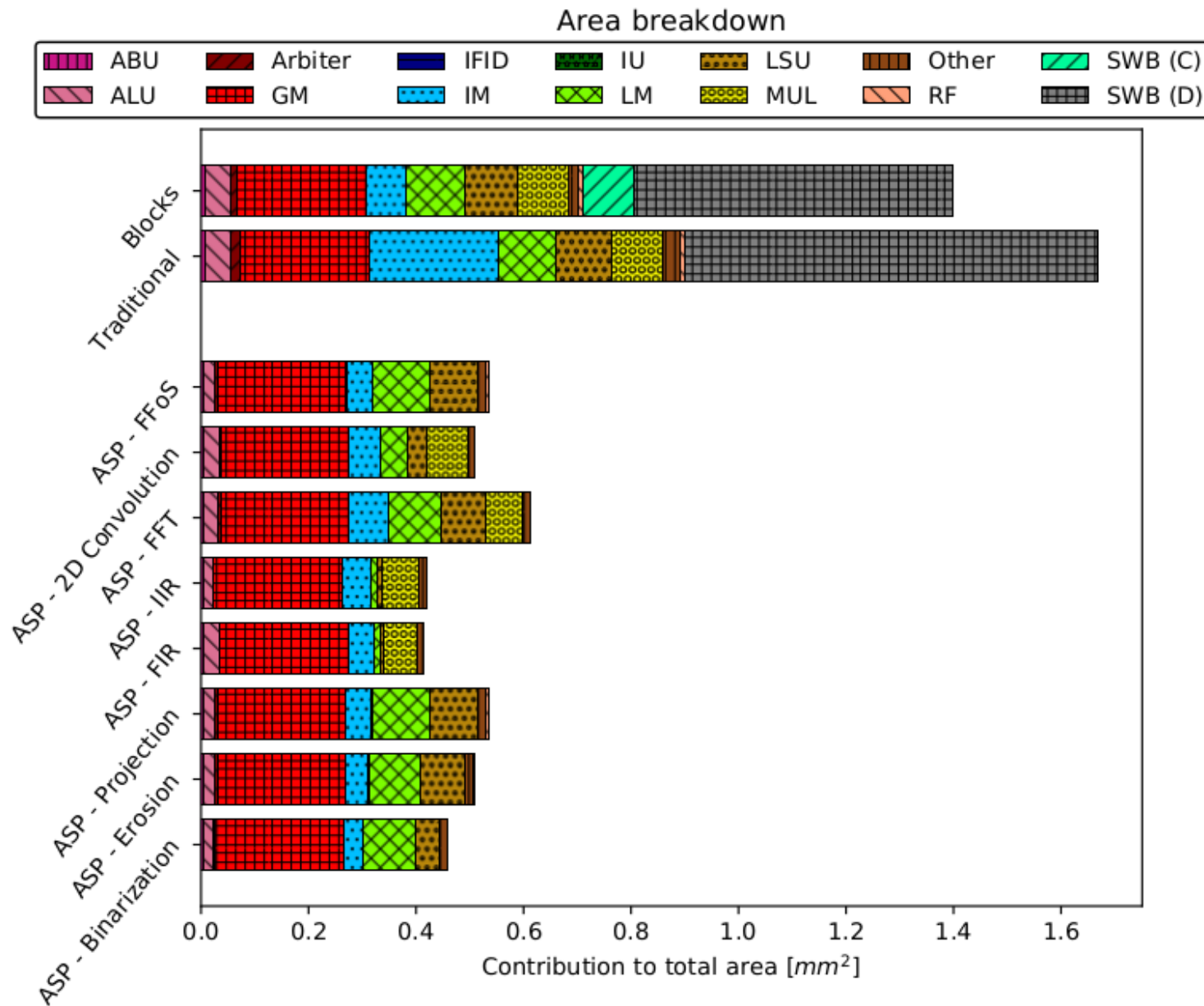
Blocks



Traditional



Results



Conclusions

- Blocks allows CGRAs to match required parallelism types closely, leading to:
- Total energy reduction between 9% and 29%.
- Overhead reduction between 46% and 76%.
- A small version of Blocks was taped-out and shown working. Larger version in progress.

Thank you for your attention

- Any questions?

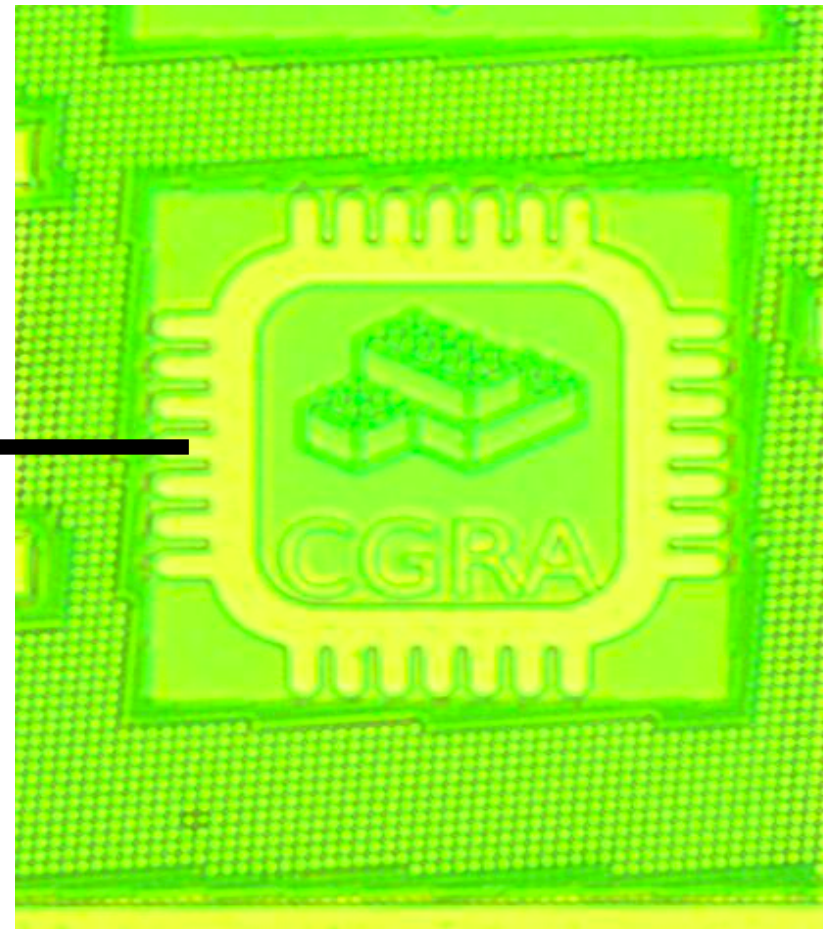
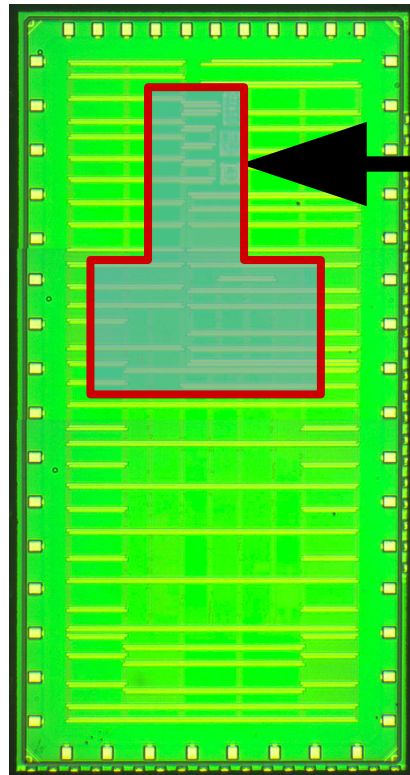
Chip info:

Area: 1.92 x 3.84mm

Power: 157.2 mW

3*ARM Cortex-M0

1*CGRA



Backup slides

Toolflow

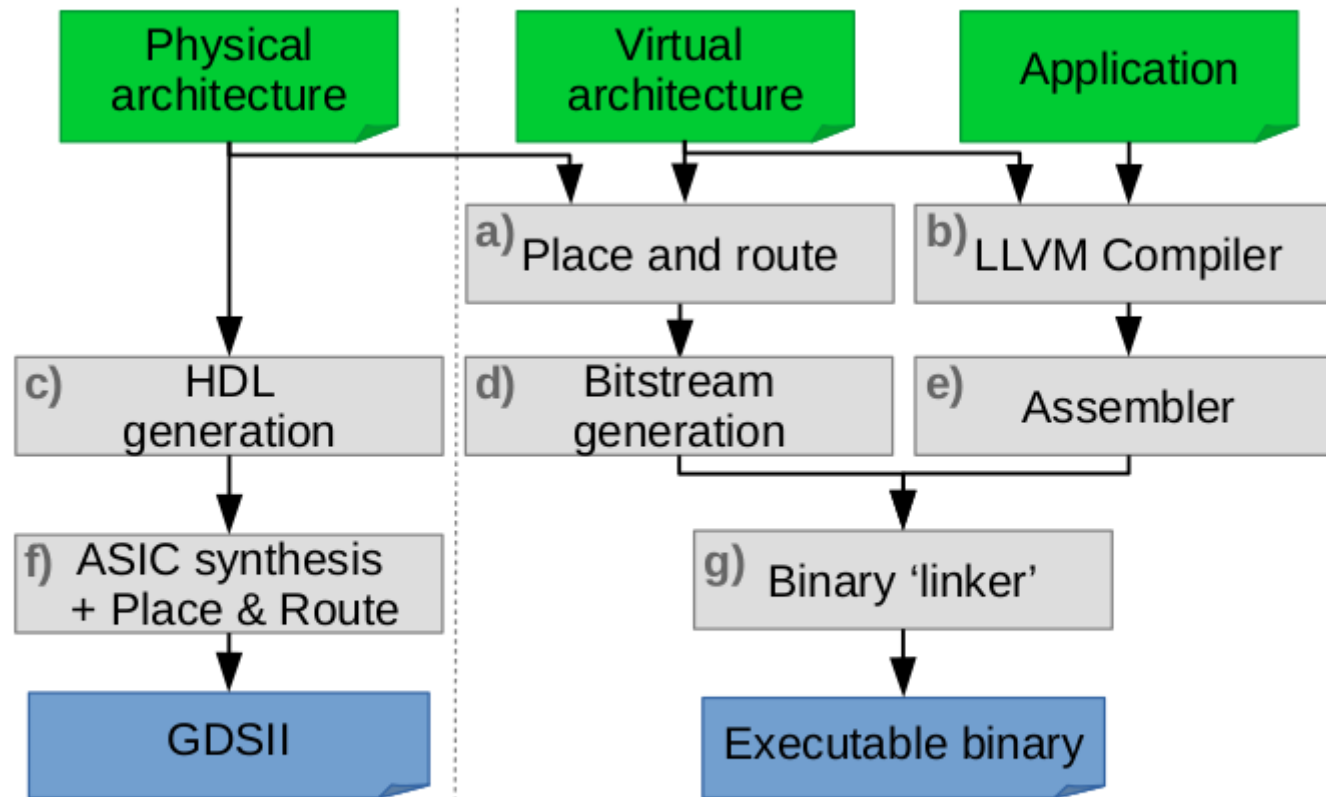


Fig. 3: The Blocks tool-flow

Inside a function unit

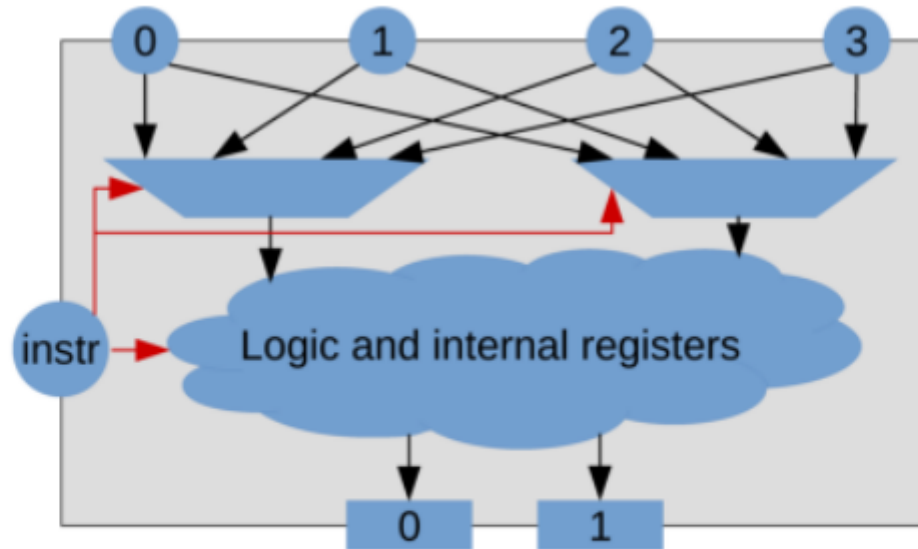


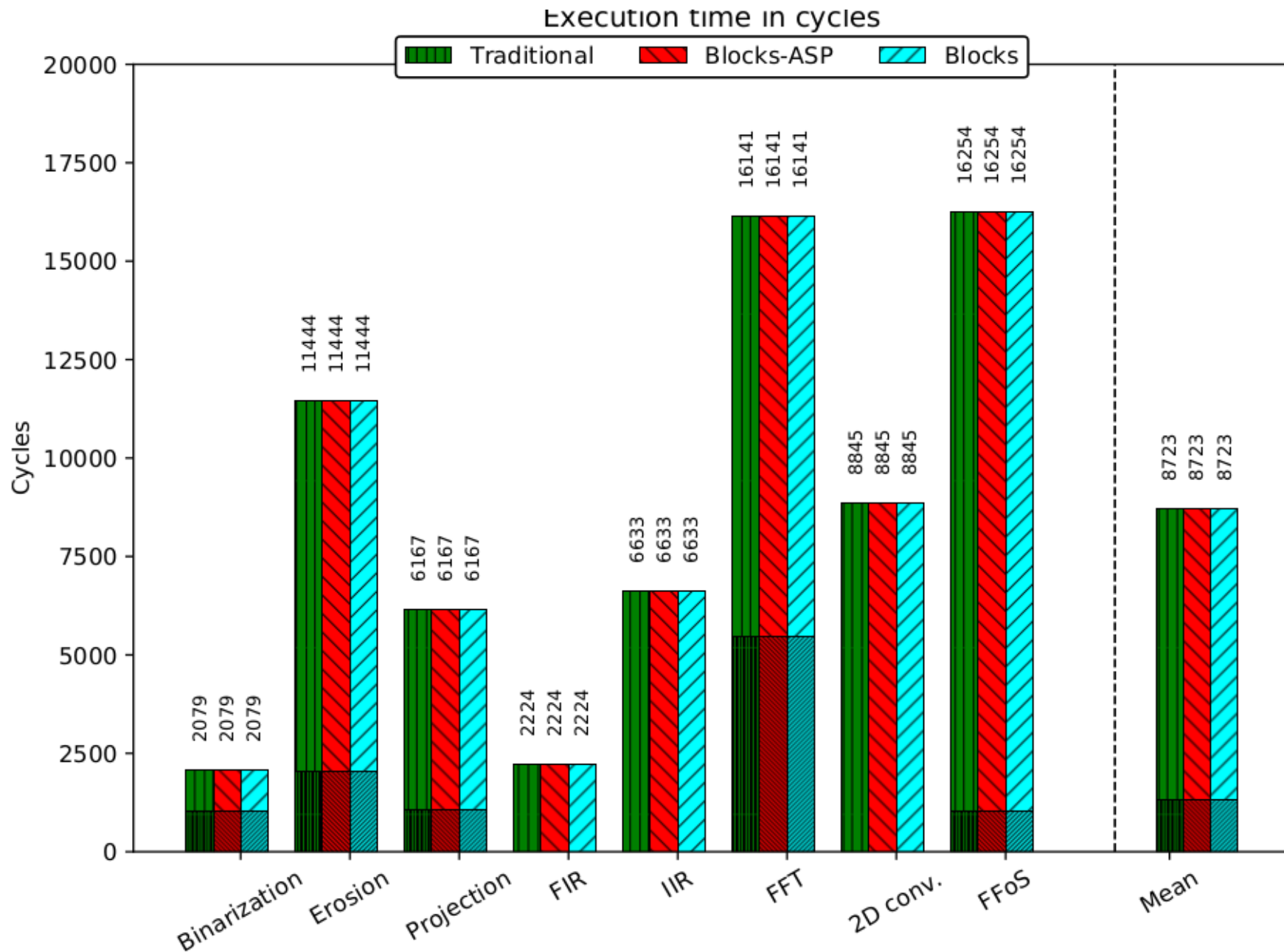
Fig. 2: Functional unit with 4 inputs and 2 outputs.

Benchmark kernels

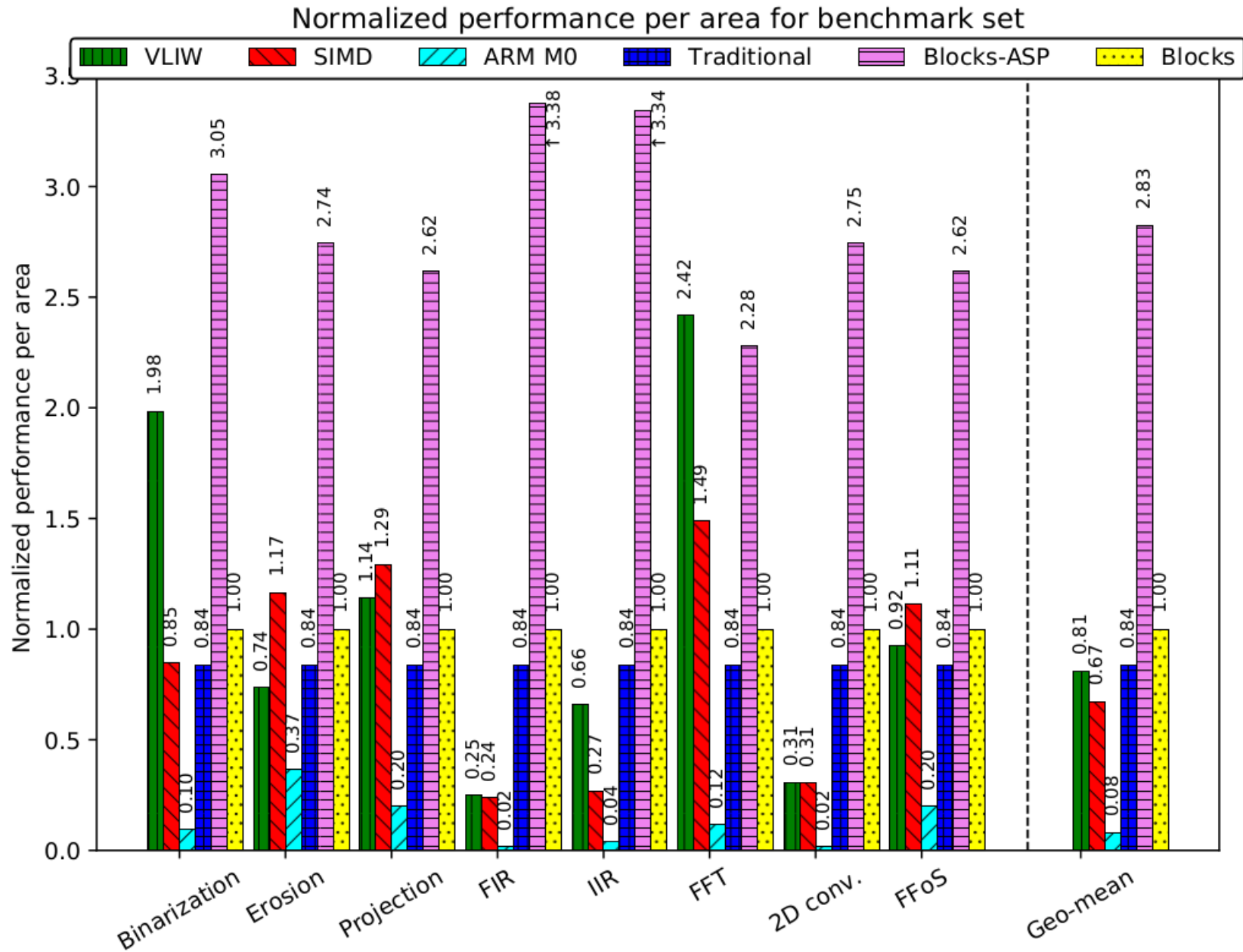
Benchmark	Description	Type	Data size
<i>Binarization</i>	Thresholding on greyscale image	scalar to scalar	128*64 pixels (8 bit)
<i>Erosion</i>	Noise removal by AND-ing neighbouring pixels	3*3 window to scalar	128*64 pixels (8 bit)
<i>Projection</i>	Sums each horizontal and vertical row/column	vector to scalar	128*64 pixels (8 bit)
<i>FIR</i>	8-tap low-pass FIR filter on input signal	8*1 convolution	2200 samples (32-bit)
<i>FIR</i>	3rd order low-pass filter on input signal	2*1 + 2*1 convolution	2200 samples (32-bit)
<i>FFT</i>	8-point complex FFT on audio signal	8*1 to 8*1 vector (complex)	2200 samples (32-bit)
<i>2D convolution</i>	Gaussian blur on image	3*3 window to scalar	128*64 pixels (8 bit)
<i>FFoS</i>	Industrial vision application	image to 2 8*1 vectors	128*64 pixels (8 bit)

Table 6.1: Overview of benchmark kernels

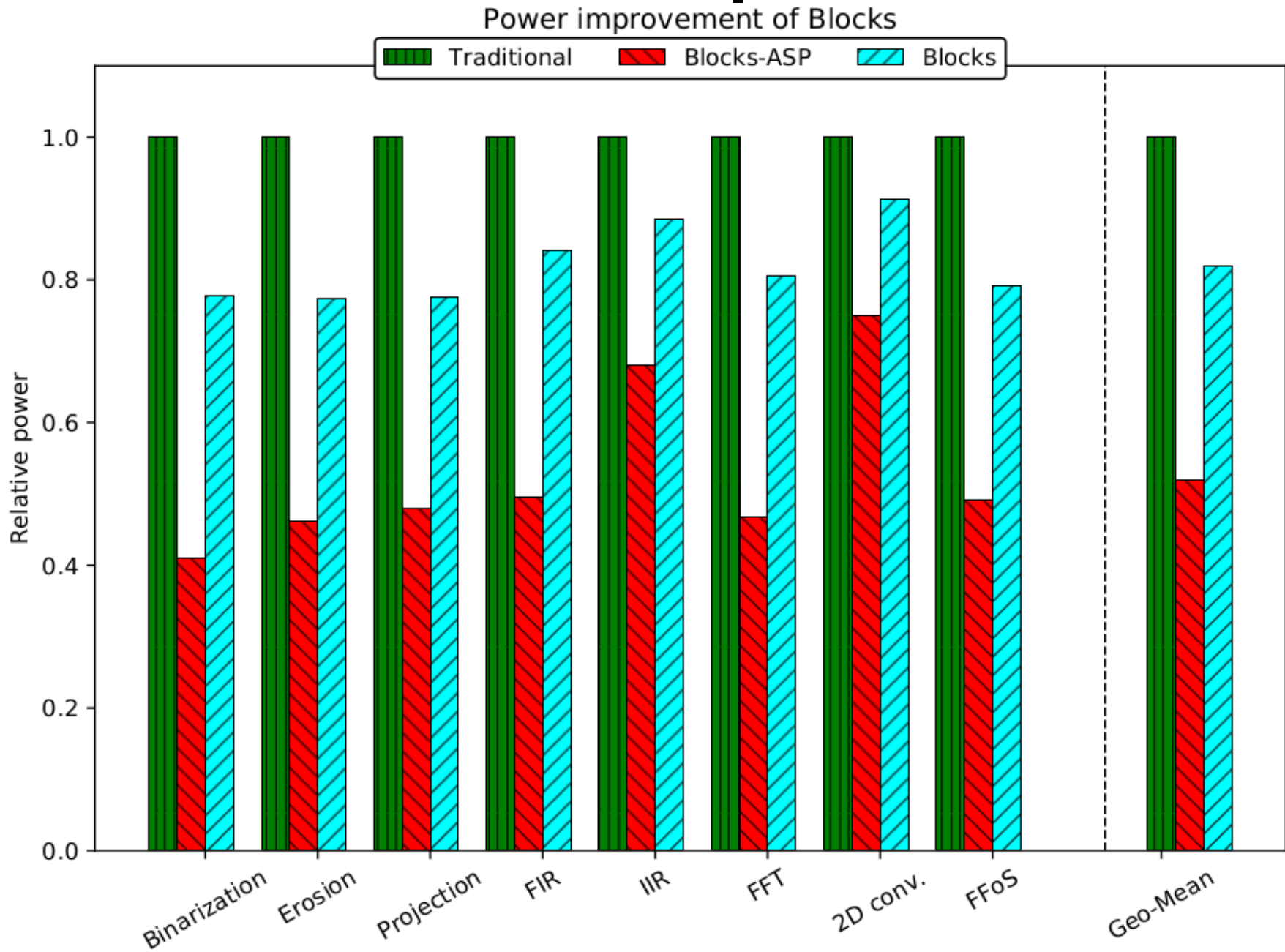
Performance



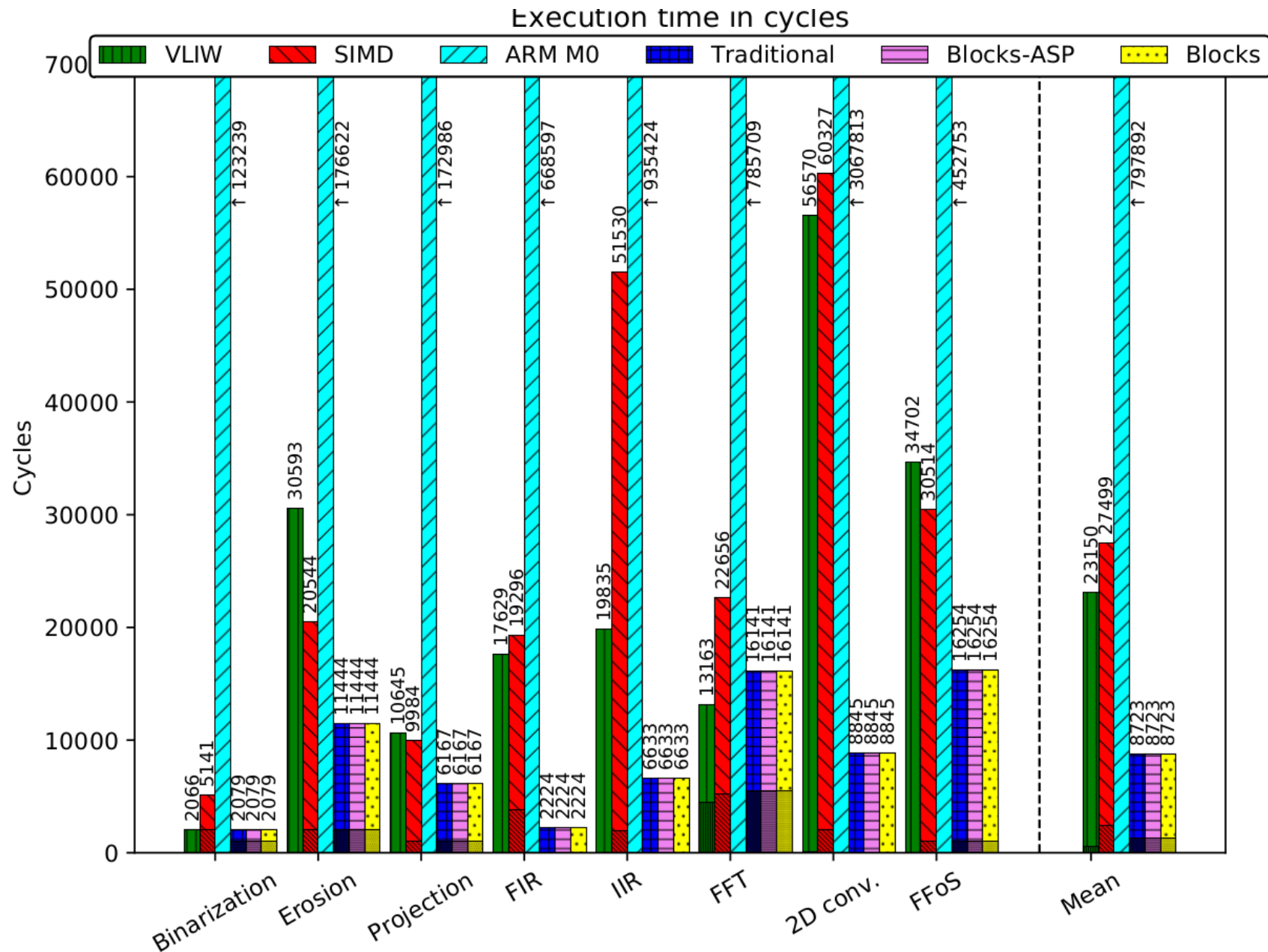
Performance per area



Relative power



Performance (SIMD + VLIW+ ARM M0)



Energy (SIMD + VLIW+ ARM M0)

Energy for executing benchmark in nanojoule

