AIM: Accelerating Arbitrary-precision Integer Multiplication on Heterogeneous Reconfigurable Computing Platform Versal ACAP

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https://peipeizhou-eecs.github.io/ https://github.com/arc-research-lab/AIM



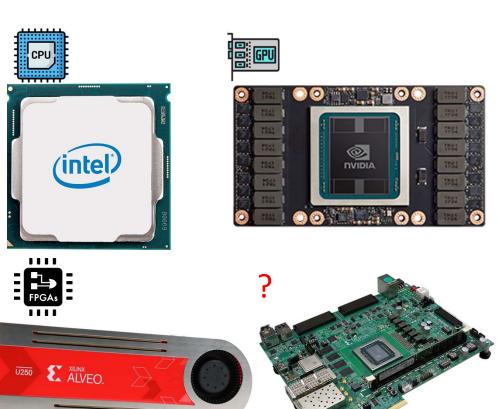




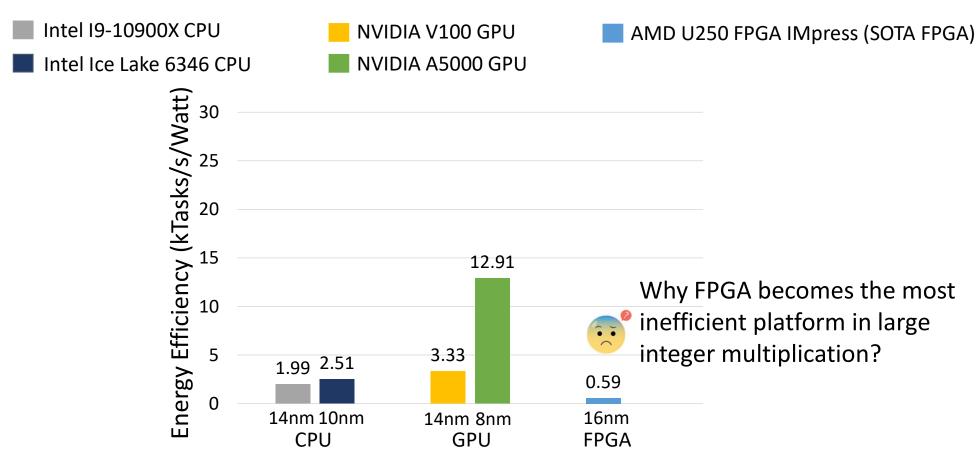


Arbitrary Precision Integer Multiplication

Ising Theory
Number Theory
Planetary Orbit
Security
System
Quantum Information
Bioinformatics
Homomorphic Encryption
Simulation
Physics









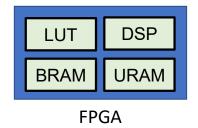
Load/Store

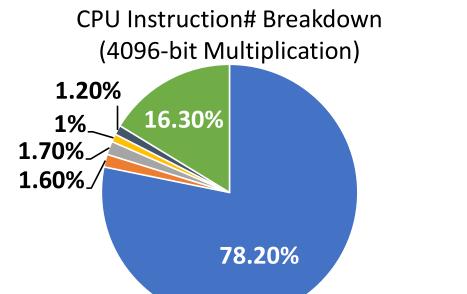
Others





VS





Carry Propagation

Pre-processing

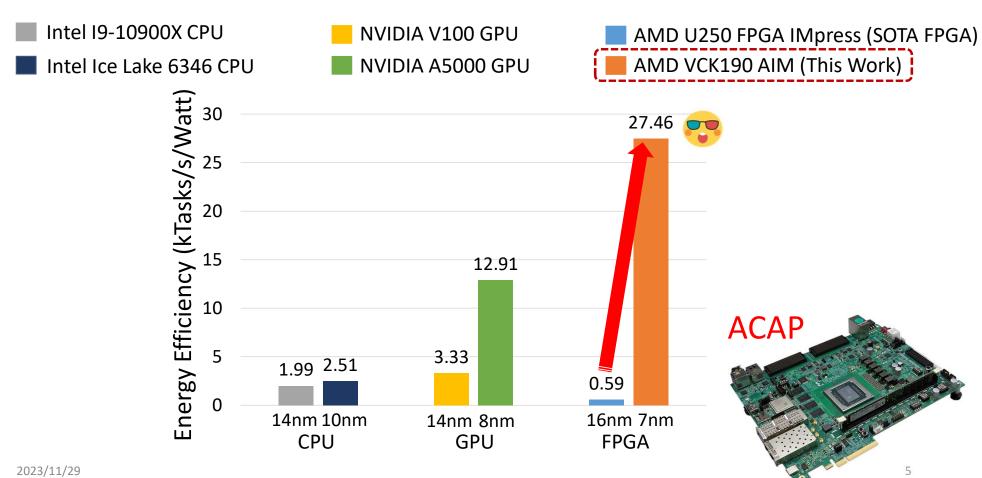
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AVX-IFMA

Init

ACAP: FPGA + Vector Units

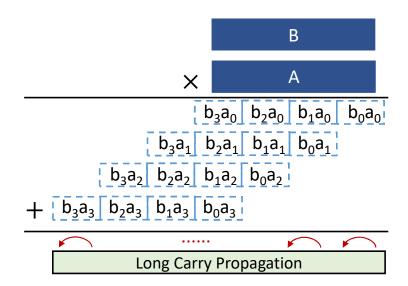




Schoolbook Decomposition

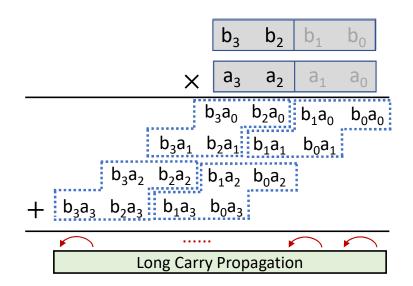


Decomposition Method



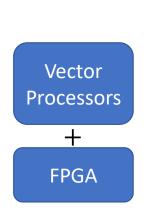
Background

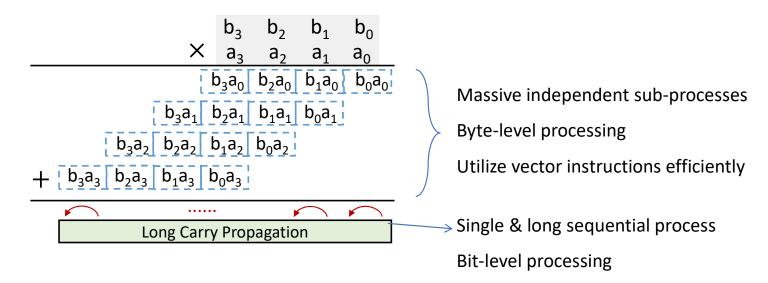






Combination of massive parallelism and long sequential process



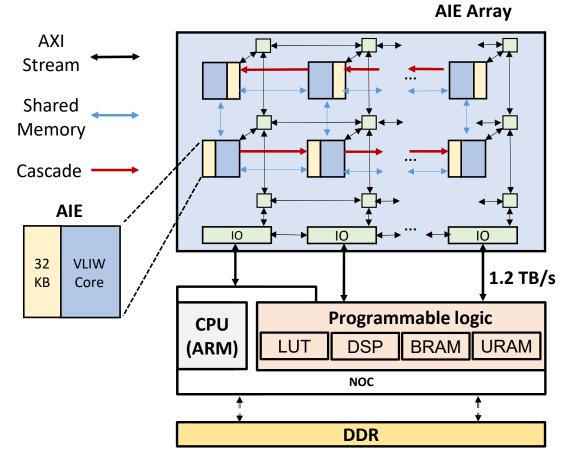




- Can FPGAs take advantage of vector processing?
- Will heterogeneity bring performance or energy efficiency gains?
- How to find the best mapping strategy? Programming Efforts? Etc.

Versal ACAP Architecture

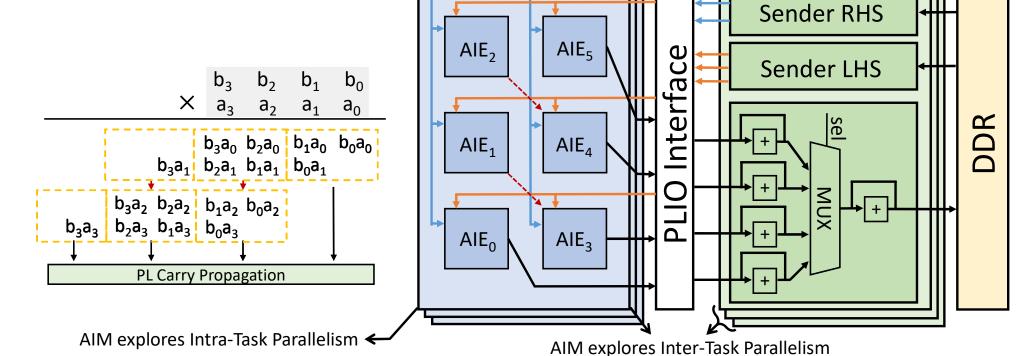




AIM Architecture





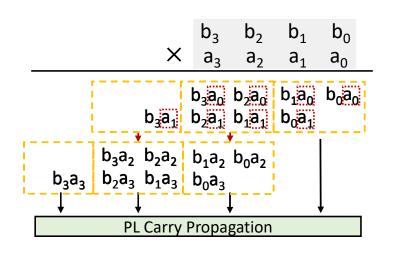


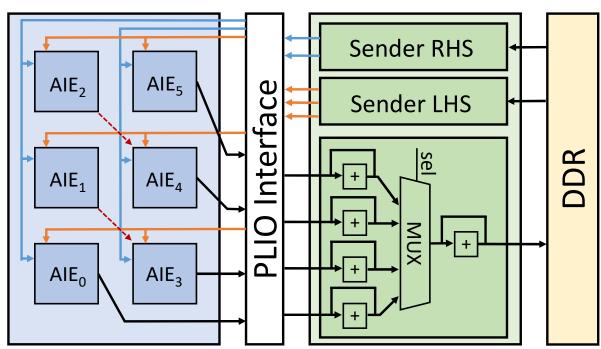
Less hardware resources; Use more AIEs; Low AIE kernel efficiency;

AIM Architecture



AIM Mapping Strategy 1





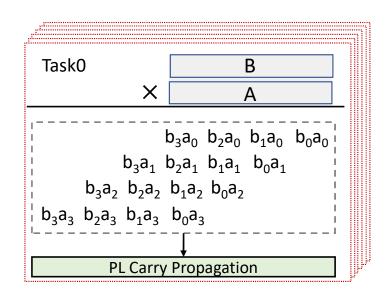
Less hardware resources; Use more AIEs; Low AIE kernel efficiency;

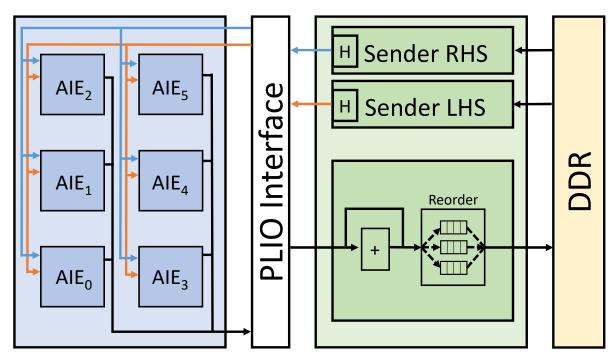


AIM Architecture



AIM Mapping Strategy 2





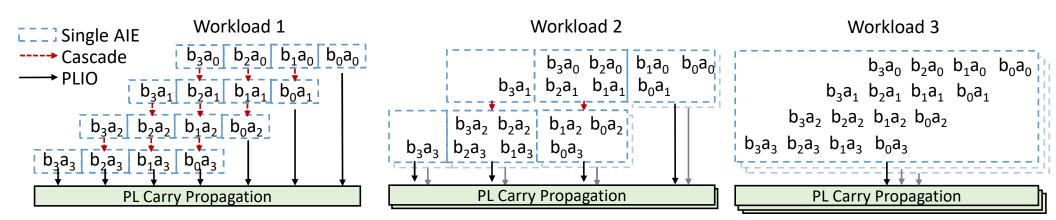
 C_2 , C_4 , C_1 , C_5 , C_0 , $C_3 \Longrightarrow C_0$, C_1 , C_2 , C_3 , C_4 , C_5

More hardware resources; Use less AIEs; High AIE kernel efficiency;

Workload Partition in AIM

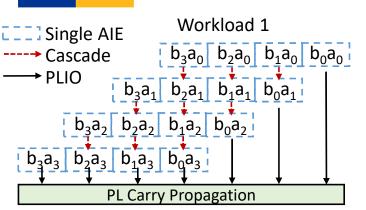
University of Pittsburgh

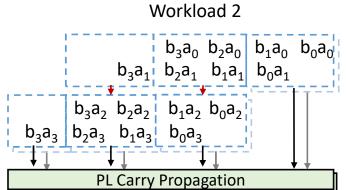
- Maximum Intra-task Parallelism
- Maximum Inter-task Parallelism
- Hybrid Parallelism

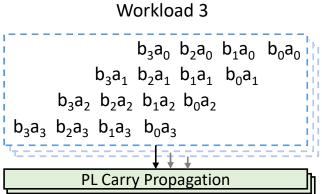


Workload Partition in AIM









System level performance of 8192-bit Multiplier

Case	$\mid P_{Intra}$	P_{Inter}	#bits/AIE	PKT	LUT	BRAM	Tasks/s
306 AIEs are used 1	306	1	496	1	43.6%	4.7%	1.6M Low kernel efficiency
210 AIEs are used ★ 2	30	7	1736	1	78.1%	16.7%	9.6M
Only 80 AIEs are used 3	1	80	8192	4	60.5%	98.6%	5.7M High kernel efficiency

Single AIE Design

```
Listing 1 Data tiling and dataflow in AIM.

L3: PL_load_input_data_from_DDR(...);

L2: data_preprocessing_on_PL(...);

L1: // Parallel computation in AIE array

for(int c = 0; c < AIE_COL; c++):

// Dependency exists on different rows

for(int r = 0; r < AIE_ROW; ++r):

L0: // Single AIE compute flow

for(int w = 0; w < B_W/P_W; ++w):

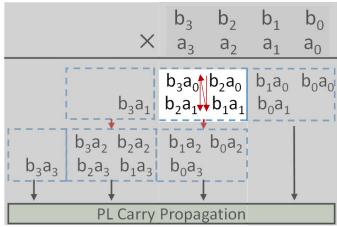
for(int h = 0; h < A_H/P_H; ++h):

vector_mul(...); //call packed instr.

L2: carry_propagation_on_PL(...);

L3: PL_store_results_DDR(...);
```





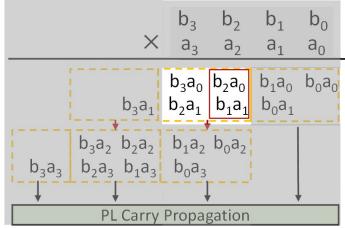


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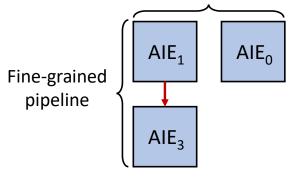
Scaling Out to AIE Array in AIM

Listing 1 Data tiling and dataflow in AIM. L3: PL_load_input_data_from_DDR(...); L2: data_preprocessing_on_PL(...); L1: // Parallel computation in AIE array for(int c = 0; c < AIE_COL; c++): // Dependency exists on different rows for(int r = 0; r < AIE_ROW; ++r): L0: // Single AIE compute flow for(int w = 0; w < B_W/P_W; ++w): for(int h = 0; h < A_H/P_H; ++h): vector_mul(...); //call packed instr. L2: carry_propagation_on_PL(...); L3: PL_store_results_DDR(...);





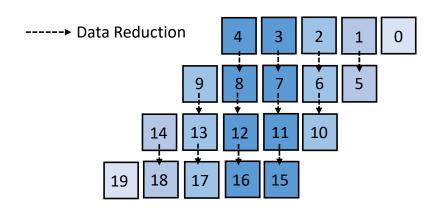
Parallel Compute

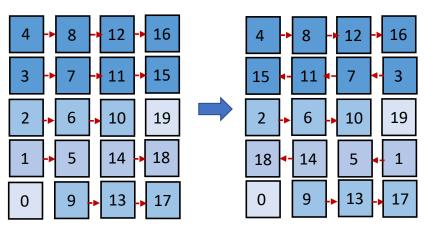


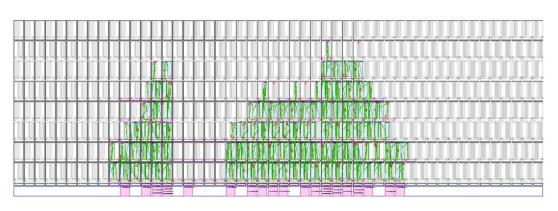
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Scaling Out to AIE Array in AIM









Up to 396 AIEs can be used



Fine-Grained Pipeline in AIM



Listing 1 Data tiling and dataflow in AIM.

```
L3: PL_load_input_data_from_DDR(...);

L2: data_preprocessing_on_PL(...);

L1: // Parallel computation in AIE array

for(int c = 0; c < AIE_COL; c++):

// Dependency exists on different rows

for(int r = 0; r < AIE_ROW; ++r):

// Single AIE compute flow

for(int w = 0; w < B_W/P_W; ++w):

for(int h = 0; h < A_H/P_H; ++h):

vector_mul(...); //call packed instr.

L2: carry_propagation_on_PL(...);

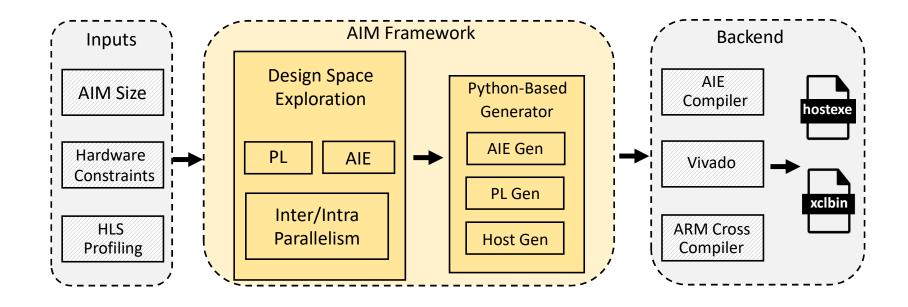
L3: PL_store_results_DDR(...);
```

DDR Reorganize/Header AIE Carry/Reorder **DDR**

All modules are coordinated in a fine-grained pipeline

AIM Framework





https://github.com/arc-research-lab/AIM



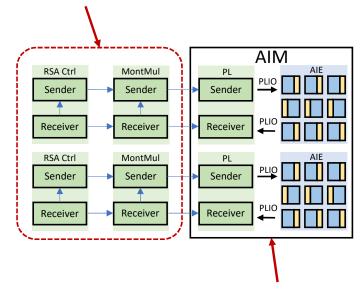
Applications - RSA



```
ciphertext = plaintext^{E} \% N
plaintext = ciphertext^{D} \% N
```

Application specific control logic can be easily integrated into the pipeline

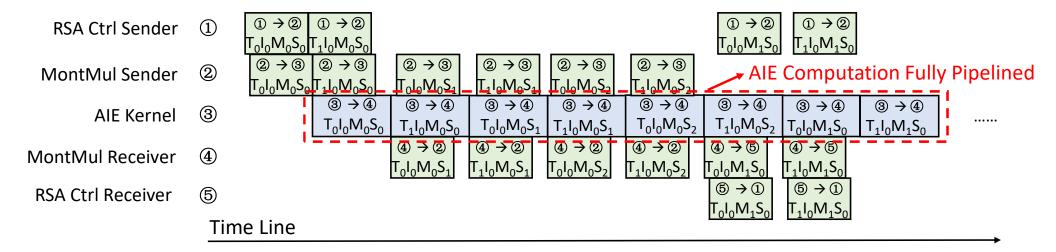
```
// T is plaintext or ciphertext
// E, n, p are key-related parameters
RSA(T, E, n, np):
    T_m = \text{Enter\_Montgomtry\_Space}(T, n, np)
    res = Montgometry_One()
    while (e > 0):
        if (e&1):
             res = MontMul(res, T_m, n, np)
        T_m = \text{MontMul}(T_m, T_m, n, np)
        e >>= 1:
    res = Exit_Montgomtry_Space(res, 1, n, np)
    return res
// a_m, b_m are k-bit integers
MontMul(a_m, b_m, n, np):
    d = a_m * b_m;
    c = np * d_{low}; — multiplications
    f = c_{low} * n;
    g = (f + d) >> k;
    g = (g > m) ? g - m:g;
    return g;
```



optimized multiplication kernels

Applications - RSA





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Applications - Mandelbrot Set

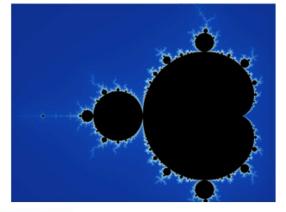


Mandelbrot set

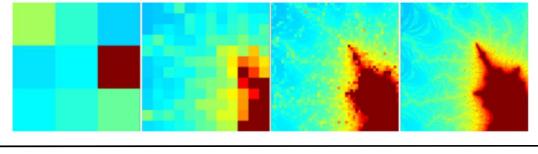
- divergence tests of sampled points on the complex plane
- detailed structures at arbitrary precision

$$f_c(0), f_c(f_c(0)), f_c(f_c(f_c(f_c(0)))), \dots$$

 $f_c(z) = Z^2 + C$



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Increase Precision

Experiment setup



- Implemented Platform: AMD Versal VCK190
- Frequency: AIE@1GHz, PL@160~220MHz
- Software Tools: Vitis 2021.1
- Applications: Large Integer Multiply, RSA, Mandelbrot Set
- Baseline
 - CPU: Intel Xeon Gold 6346, GMP 6.2.1
 - GPU: NVIDIA A5000, CGBN 2.0

Analytical Model Accuracy



- AIM predicts performance accurately for different configurations
- AIM can find optimal configuration quickly
 Comparison between AIM modeling & on-board measurement

P_{Intra}	P_{inter}	#bits/AIE	Freq.	Model	On-board	Error
20	8	16616	175	185.7k	186.2k	0.3%
30	7	13144	176	255.5k	256.2k	0.3%
42	6	11160	184	299.6k	302.2k	0.8%
56	5	9424	190	344.4k	348.3k	1.1%
72	4	8432	190	340.0k	344.5k	1.3%
90	4	7440	186	430.1k	436.6k	1.5%
110	3	6696	207	392.6k	399.1k	1.7%
132	3	6200	209	452.8k	459.8k	1.5%
156	2	5704	206	352.1k	356.5k	1.3%
182	2	5208	207	415.9k	387.3k	-6.9%
210	1	4712	206	249.4k	254.5k	2.0%
272	1	4216	208	280.3k	270.6k	-3.5%

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Performance & Energy Eff. Comparison



- AIM is more energy efficient than CPU and GPU
- AIM supports much larger multiplications than GPU

Comparison among optimal AIM implementation, Intel Xeon 6346 CPU, and Nvidia A5000 GPU for LIM with input sizes from 4,096 to 262,144 bit

	CPU (32 cores, 410W)		GPU (230W)		AIM (<77W)		Energy Eff. Gain	
Input Bits	kTasks/s	kTasks/s/Watt	kTasks/s	kTasks/s/Watt	kTasks/s	kTasks/s/Watt	AIM vs CPU	AIM vs GPU
4,096	23,259	56.73	145,474	632.50	17,685	467.87	8.25x	0.74x
8,192	7,619	18.58	36,760	159.83	9,578	220.04	11.84x	1.38x
16,384	2,726	6.65	11,355	49.37	3,901	84.02	12.63x	1.70x
32,768	1,026	2.50	2,970	12.91	1,438	27.46	10.96x	2.13x
65,536	386.0	0.94	×	×	459.8	6.86	7.29x	×
131,072	145.3	0.35	×	×	128.1	1.75	4.93x	×
262,144	57.0	0.14	×	×	33.8	0.44	3.15x	<u> </u>

Performance & Energy Eff. Comparison



AIM is efficient in end-to-end applications

Performance & energy efficiency comparison between CPU GMP and AIM for RSA

CPU			AIM			
Input Bits	Tasks/s	Tasks/s/Watt	Tasks/s	Tasks/s/Watt		
4,096	6124	14.97 (1x)	81734	2458.2 (162.6x)		
8,192	930	2.27(1x)	44737	1196.2 (527.2x)		
16,384	161	0.39(1x)	19017	435.2 (1109.2x)		
32,768	28	0.07(1x)	10639	134.8 (1966.6x)		

Performance & energy efficiency comparison between CPU GMP, GPU CGBN and AIM for plotting Mandelbrot set

	CPU			GPU	AIM		
Input Bits	Tasks/s	Tasks/s/Watt	Tasks/s	Tasks/s/Watt	Tasks/s	Tasks/s/Watt	
8,192	0.048	0.0037 (1x)	6.790	0.0326 (8.80x)	0.641	0.0228 (6.15x)	
16,384	0.016	0.0013(1x)	1.799	0.0087(6.74x)	0.241	0.0088 (6.85x)	
32,768	0.006	0.0005 (1x)	0.509	0.0024 (4.99x)	0.126	0.0042 (8.62x)	

ARC-LAB



THANK YOU!







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Github Repo: https://github.com/arc-research-lab/AIM



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