C AND OPENCL GENERATION FROM MATLAB

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SPeCS
Special-Purpose Computing
Systems, languages and tools

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OUTLINE

- Introduction
- Motivation
- MATISSE OpenCL back-end
- Results
- Conclusions and Future Work

THE AGE OF PARALLELISM – CPU

- Parallelism in CPUs
  - SIMD: **Data parallelism** on a single thread
  - Multicore: Requires **Task parallelism**.
- Both are required for maximum efficiency.

THE AGE OF PARALLELISM – GPU

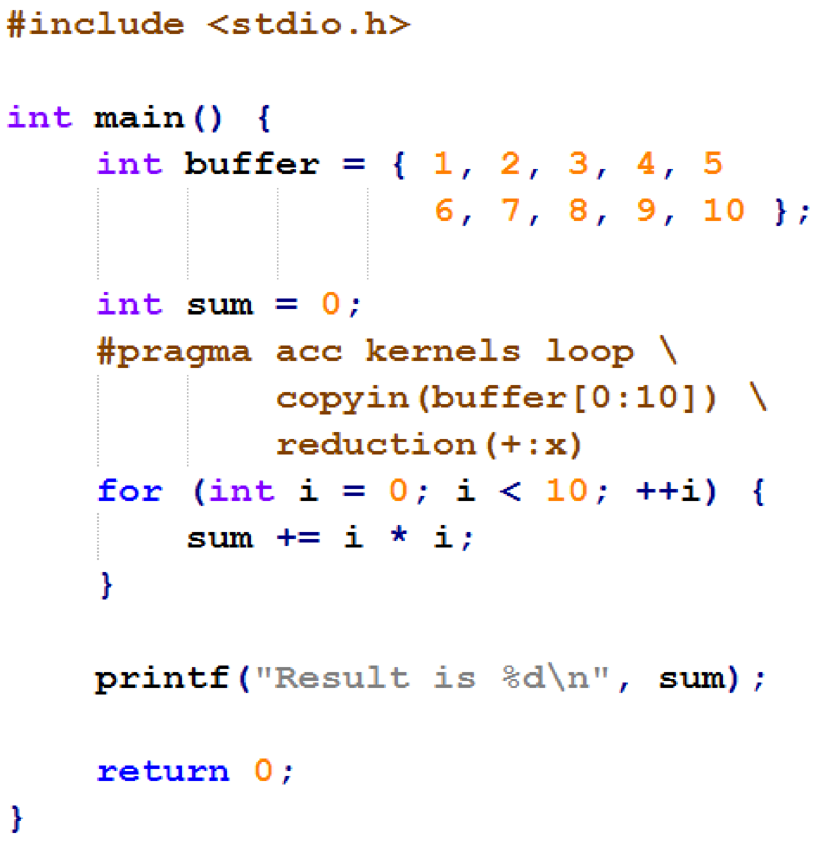
- Initially GPUs mostly used for graphical computing
  - Could be used for other operations, but that was far too much work
  - Usually have their own memory
- GPGPUs: **General-Purpose** Graphics Processing Unit
  - Still focused on graphics, still tend to have a separate memory
  - Easier to program now
- GPGPUs require parallelism:
  - Take longer than CPUs for sequential tasks
  - With parallelism, speedups of 1000x are possible

PROGRAMMING MODELS – DIRECTIVE-DRIVEN

- Some approaches let the programmer specify parallelism declaratively
    - “This part of the code can be made parallel”
    - Acceptable performance with relatively small effort.
    - Code is annotated with “directives” – code that is recognized by the compiler
    - Examples are OpenMP and OpenACC

PROGRAMMING MODELS – OPENACC

- Directive-driven extensions for C, C++ or FORTRAN.
- Compilers automatically generate the GPGPU code and communications.
- Suitable for accelerators, including GPGPUs
    - Data-transfers are explicit, using copyin, copyout, copy and present.



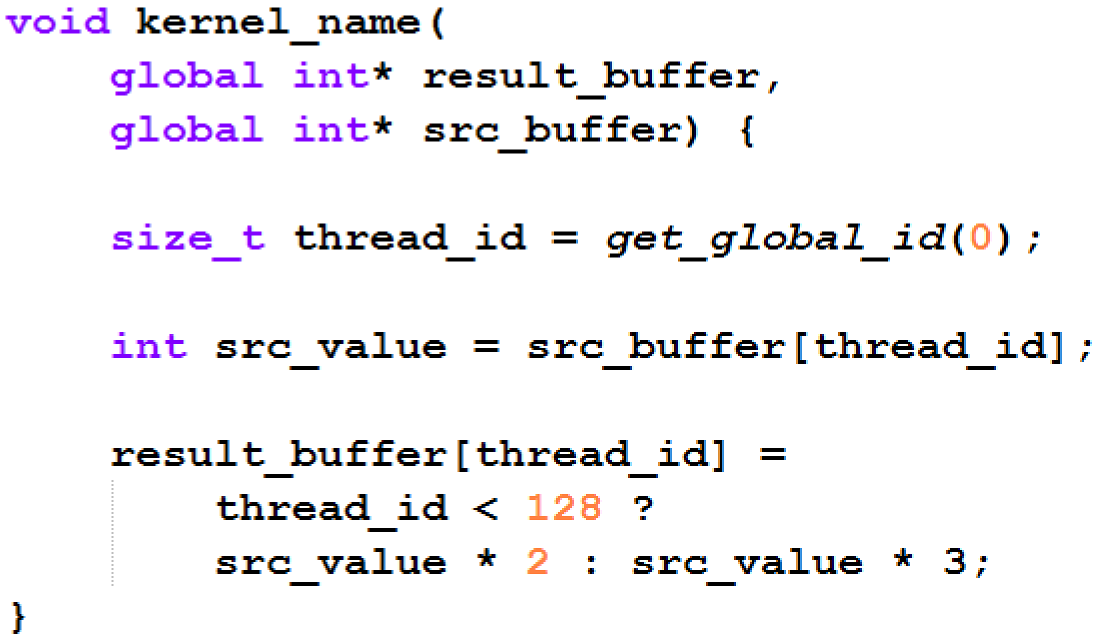
```
#include <stdio.h>

int main() {
    int buffer = { 1, 2, 3, 4, 5
                   6, 7, 8, 9, 10 };

    int sum = 0;
    #pragma acc kernels loop \
            copyin(buffer[0:10]) \
            reduction(+:x)
    for (int i = 0; i < 10; ++i) {
        sum += i * i;
    }

    printf("Result is %d\n", sum);

    return 0;
}
```

PROGRAMMING MODELS – LANGUAGES

- Old days:
  - Shader languages: HLSL, GLSL
- More recently:
  - GPGPU-specific languages: CUDA, OpenCL
  - CUDA is a language by NVIDIA, extends C, C++ or Fortran
  - OpenCL is a standard by Khronos, API + C-based language

PROGRAMMING MODELS – OPENCL

- Programming language and API (C/C++ inspired)
- Initially for GPGPU, currently supports multicore CPUs and even FPGAs
- Supported by Intel, AMD, NVIDIA, ARM, Qualcomm, Apple, ALTERA and Xilinx
- Parallel parts in OpenCL, remaining code in host language (e.g., C)



```
void kernel_name(
    global int* result_buffer,
    global int* src_buffer) {

    size_t thread_id = get_global_id(0);

    int src_value = src_buffer[thread_id];

    result_buffer[thread_id] =
        thread_id < 128 ?
        src_value * 2 : src_value * 3;
}
```

MOTIVATION – MULTI-TARGET CODE

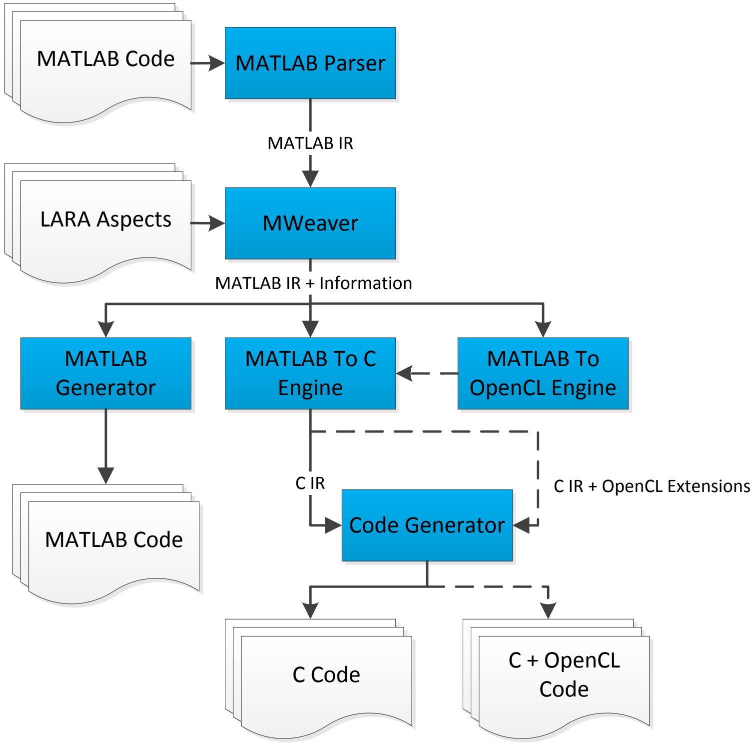
- To get the most performance we need low-level code (C, OpenCL)
- However, low-level code usually is not performance portable
- To maximize performance, different targets require different code
- Additionally, may have special requirements
    - Embedded systems without floating-point HW units, or with units that perform poorly
    - HW synthesis (compliance to different tools)

MOTIVATION – MULTI-TARGET CODE

- Possible Solution:
    - Start from clean implementation, specialize to target
- Problem:
    - Hard to transform low-level code, too many implementation details
- Our approach:
    - High-level description (MATLAB)
    - Augmented with information about implementation (LARA aspects)

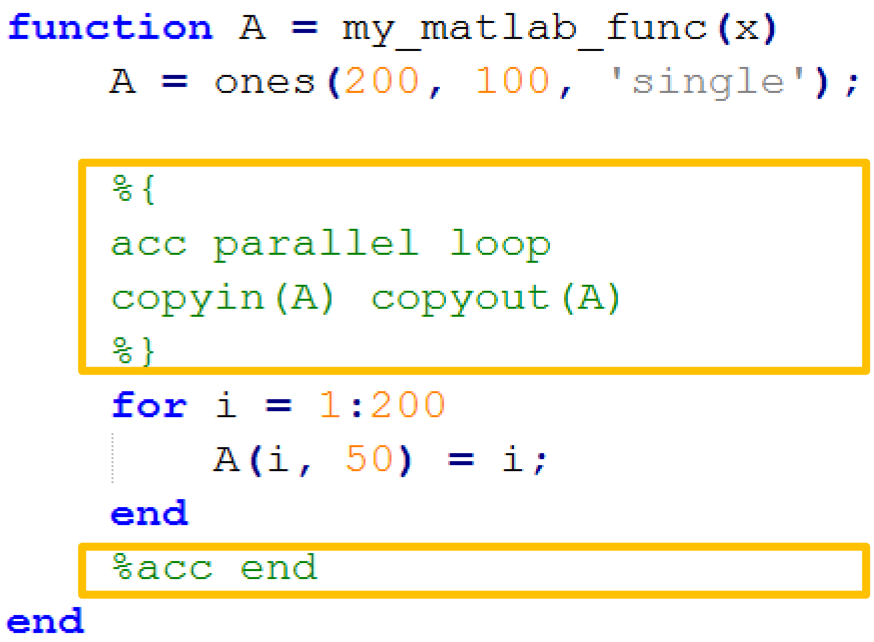
MATISSE – OPENCL BACKEND

- Proof-of-concept OpenCL backend
  - Developed during MSc
- MATLAB compiler that generates C + OpenCL code
- Based on the MATISSE framework
- MATLAB code is extended with OpenACC-based directives



MATISSE – OPENCL BACKEND

- Regions of code are marked as parallel
    - Each loop iteration is independent of the others.
- Copyin: Which variables are copied to the GPU before execution begins.
- Copyout: Which variables are copied out of the GPU after execution ends.
- Other directives are supported

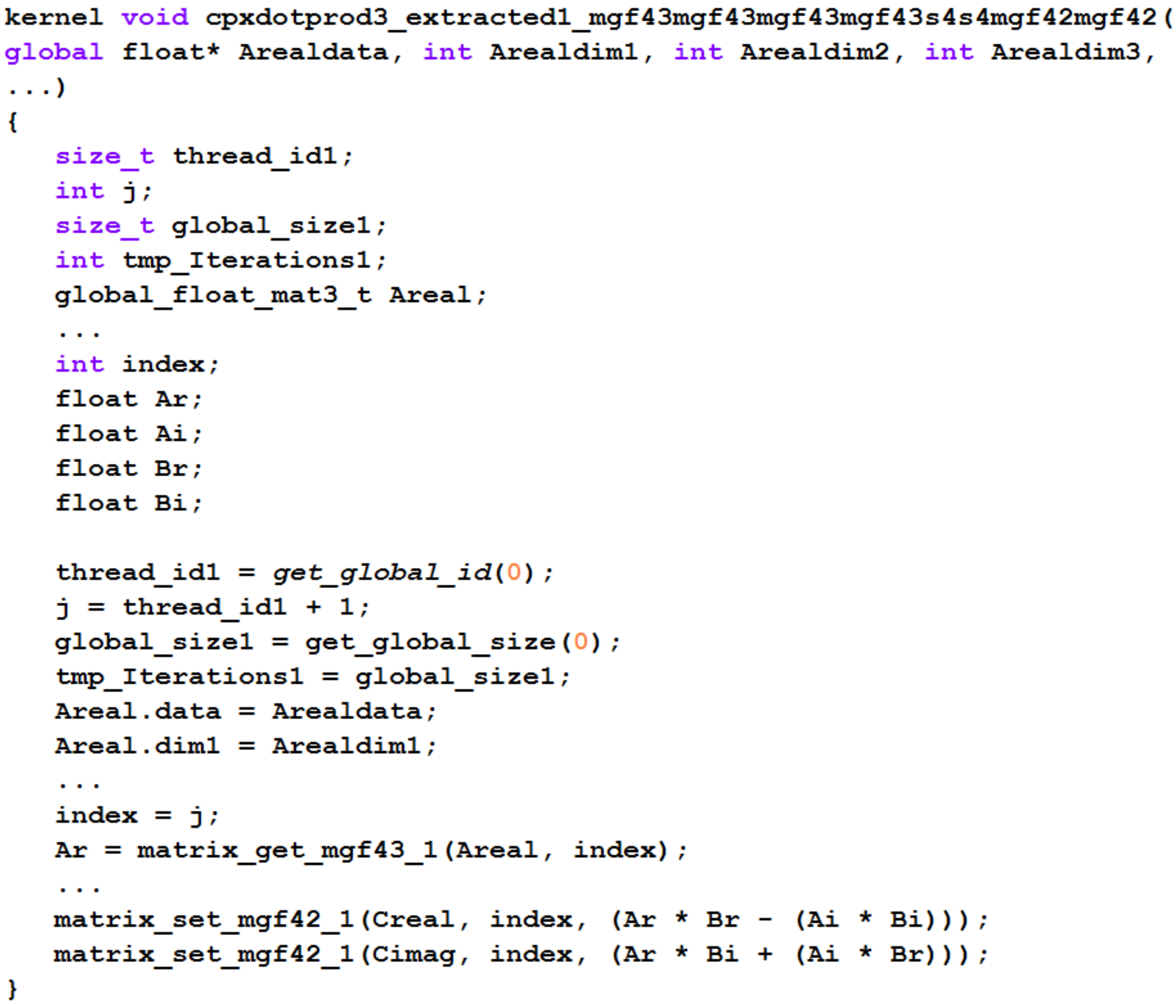


```
function A = my_matlab_func(x)
    A = ones(200, 100, 'single');

    %{
    acc parallel loop
    copyin(A) copyout(A)
    %}
    for i = 1:200
        A(i, 50) = i;
    end
    %acc end
end
```

MATISSE – OPENCL BACKEND

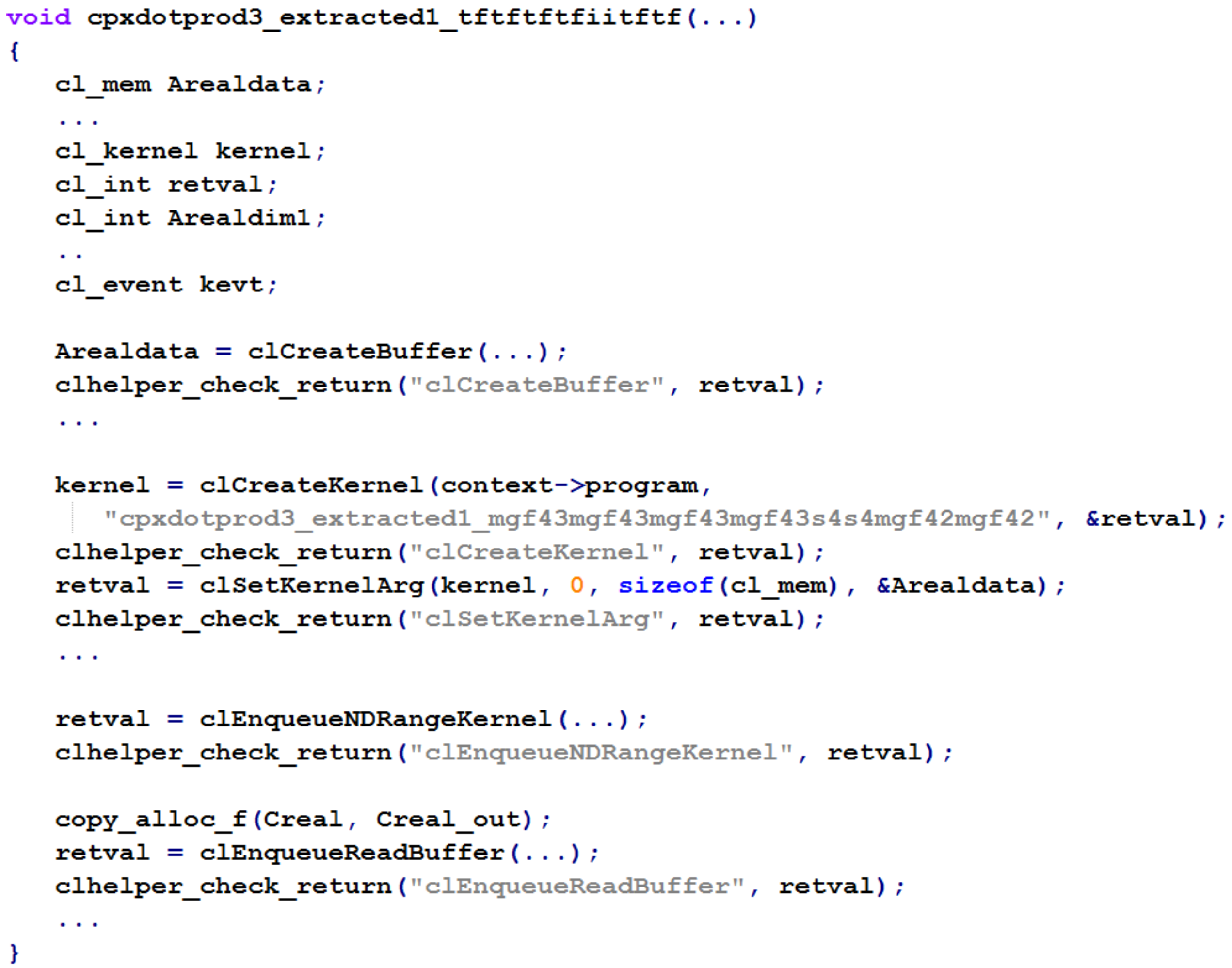
- We reuse and extend the MATISSE IRs:
    - MATLAB AST
    - C IR
- The MATISSE C backend handles sequential code sections.
- MATISSE CL overrides the code generator for the outlined functions.
    - Generates the OpenCL code and the C wrappers.

GENERATED SAMPLE CODE (OPENCL)



```
kernel void cpxdotprod3_extracted1_mgf43mgf43mgf43mgf43s4s4mgf42mgf42(
global float* Arealdata, int Arealdim1, int Arealdim2, int Arealdim3,
...)
{
   size_t thread_id1;
   int j;
   size_t global_size1;
   int tmp_Iterations1;
   global_float_mat3_t Areal;
   ...
   int index;
   float Ar;
   float Ai;
   float Br;
   float Bi;

   thread_id1 = get_global_id(0);
   j = thread_id1 + 1;
   global_size1 = get_global_size(0);
   tmp_Iterations1 = global_size1;
   Areal.data = Arealdata;
   Areal.dim1 = Arealdim1;
   ...
   index = j;
   Ar = matrix_get_mgf43_1(Areal, index);
   ...
   matrix_set_mgf42_1(Creal, index, (Ar * Br - (Ai * Bi)));
   matrix_set_mgf42_1(Cimag, index, (Ar * Bi + (Ai * Br)));
}
```

GENERATED SAMPLE CODE (C WRAPPER)



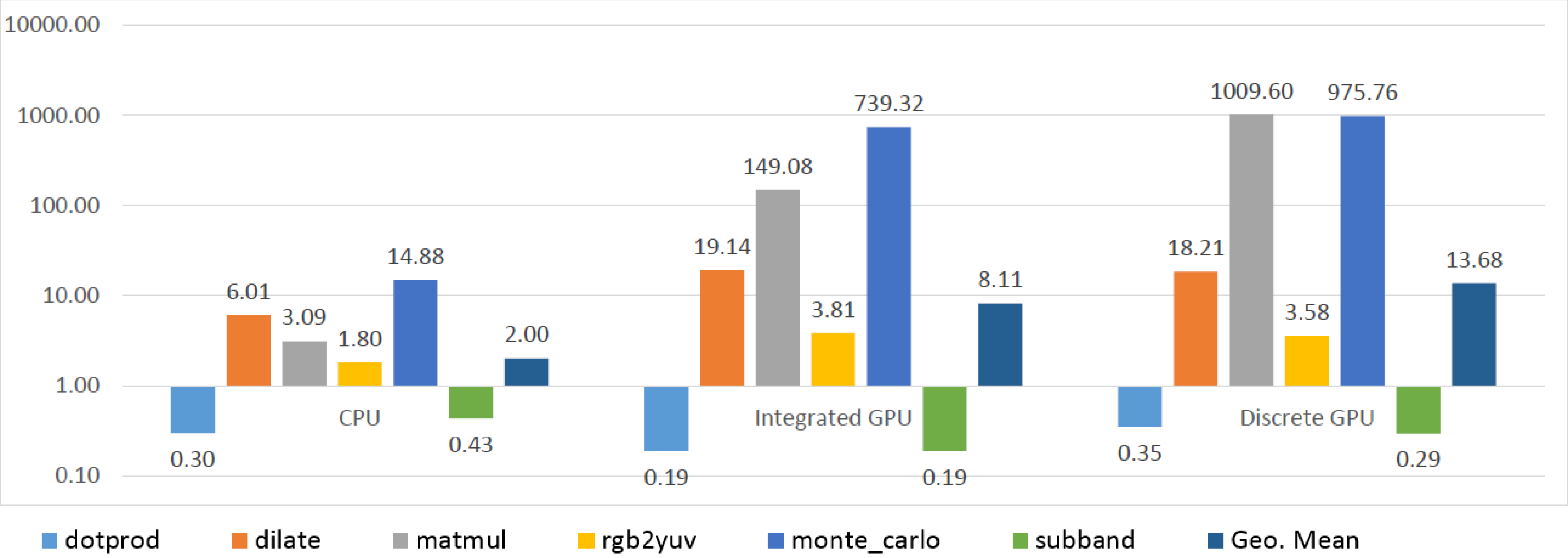
```
void cpxdotprod3_extracted1_tftftftfiitftf(...)
{
   cl_mem Arealdata;
   ...
   cl_kernel kernel;
   cl_int retval;
   cl_int Arealdim1;
   ..
   cl_event kevt;

   Arealdata = clCreateBuffer(...);
   clhelper_check_return("clCreateBuffer", retval);
   ...

   kernel = clCreateKernel(context->program,
      "cpxdotprod3_extracted1_mgf43mgf43mgf43mgf43s4s4mgf42mgf42", &retval);
   clhelper_check_return("clCreateKernel", retval);
   retval = clSetKernelArg(kernel, 0, sizeof(cl_mem), &Arealdata);
   clhelper_check_return("clSetKernelArg", retval);
   ...

   retval = clEnqueueNDRangeKernel(...);
   clhelper_check_return("clEnqueueNDRangeKernel", retval);

   copy_alloc_f(Creal, Creal_out);
   retval = clEnqueueReadBuffer(...);
   clhelper_check_return("clEnqueueReadBuffer", retval);
   ...
}
```

BENCHMARKS

- Benchmarks:
  - Reused some benchmarks already used for MATISSE C
  - Most are from embedded computing
  - Matmul: Naive implementation of matrix multiplication
  - Monte Carlo option pricing: Adapted from a MathWorks example

RESULTS – TOTAL TIME

- CPU: AMD A10-7850K@3.7GHz w/ GPU (integrated), GPU: R7 280X (discrete)
- Includes time spent on data transfers



RESULTS – MATMUL

- Modified matmul (in MATLAB) with optimizations from nVidia exemple
  - Loop Tiling
  - Local Memory

RESULTS – MATMUL

- Modified matmul (in MATLAB) with optimizations from nVidia example
  - Loop Tiling
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1024×1024	matmul (s)	matmul_nv (s)	Speedup
CPU	9.1	2.0	4.6×
GPU (int.)	0.19	0.062	3.1×
GPU (disc.)	0.028	0.035	0.8×

RESULTS – ODROID

- We were able to compile and run our programs on an Odroid board
  - ARM'sbig.LITTLE configuration and a PowerVR SGX544MP3 GPU
  - Android 4.2.2 (though we bypassed Dalvik entirely)
  - The same processor used by some smartphones.
  - Preliminary results, only
- Sadly, we were rarely able to obtain speedups
  - Only 5% faster in matrix multiplication.
  - 75% slower for the dilate benchmark.
  - Monte Carlo Option Pricing can have statistically insignificant speedups (less than 95% confidence for N = 5000), or significant slowdowns (30% slower for N = 1000)
- We hope to improve these results with future optimizations (such as thread coarsening and use of texture memory)

CONCLUSIONS

- Proof-of-concept OpenCL back-end from MATLAB
  - Based on the MATISSE framework
- Good results on desktop GPUs
- Embedded systems' SOC performance needs more time for experiments and analysis.
- Future Work:
  - Improve MATLAB compatibility (take advantage of idiomatic operations)
  - Specialize code according to target

FUTURE WORK

```
%{
acc parallel loop

copyin(readonly Areal, readonly
Aimag, readonly Breal, readonly
Bimag, numElements)

copyout(Creal, Cimag)
%}
for j=1:numElements
 index=j;
 Ar = Areal(index);
 Ai = Aimag(index);
 Br = Breal(index);
 Bi = Bimag(index);
 Creal(index) = Ar*Br-Ai*Bi;
 Cimag(index) = Ar*Bi+Ai*Br;
end
%acc end
```

```
%!parallel
Creal = Areal.*Breal-Aimag.*Bimag;
Cimag = Areal.*Bimag+Aimag.*Breal;
%!end
```

THE END

THANK YOU!

Questions?

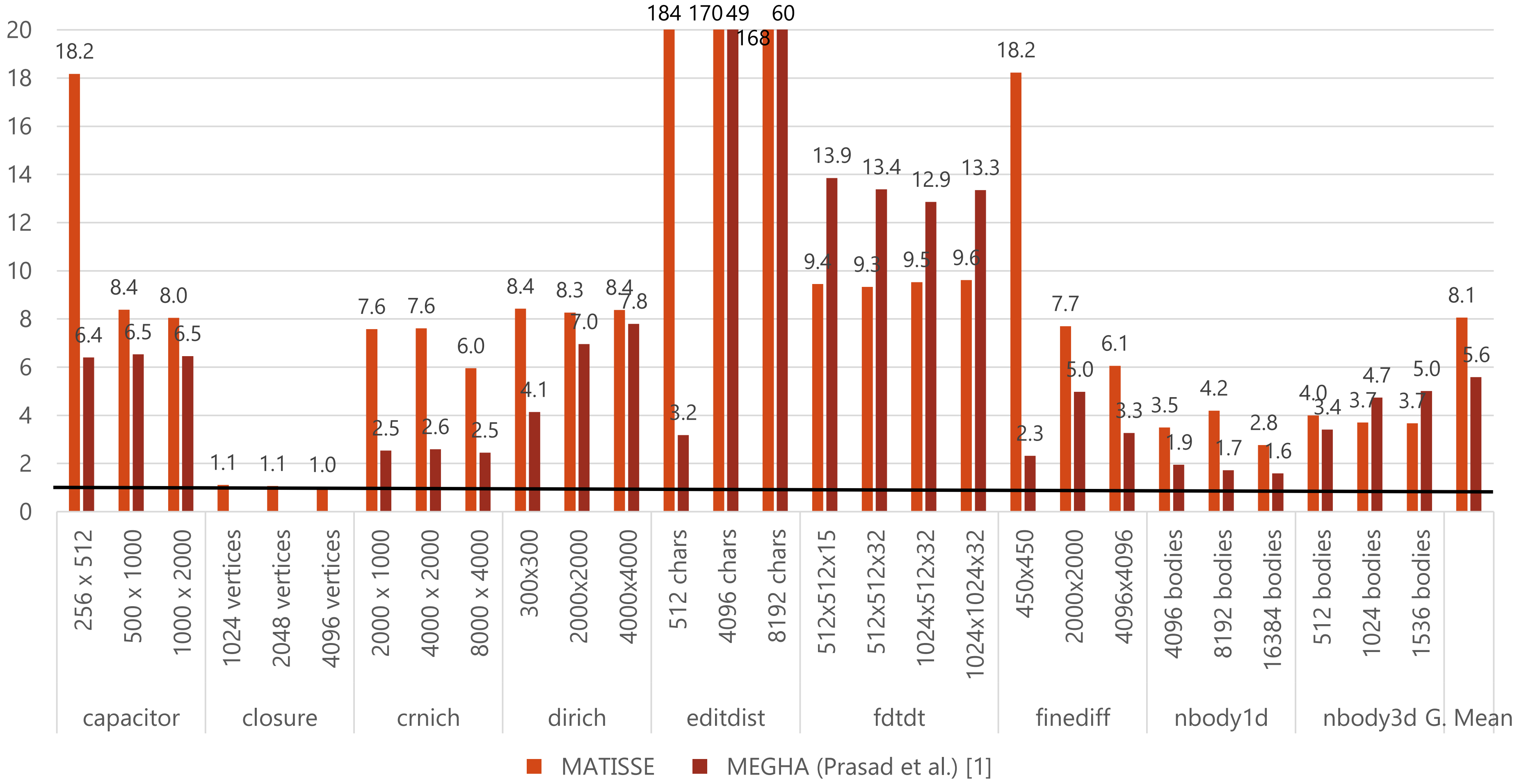
Demo of MATISSE (C only):

http://specs.fe.up.pt/tools/matisse/

RELATED WORK

- MEGHA [Prasad et al, APPLC 2012]:
  - Compiles a subset of MATLAB to CUDA
- HLLC/ParaM
  - Source-to-source [Shei et al, ICS 2011]
    - Outputs MATLAB with GPUmat API calls
  - Alternative approach: [Shei et al, INTERACT 2011]
    - Outputs MATLAB with calls to C++ and CUDA.
- Our approach: MATLAB to C + OpenCL

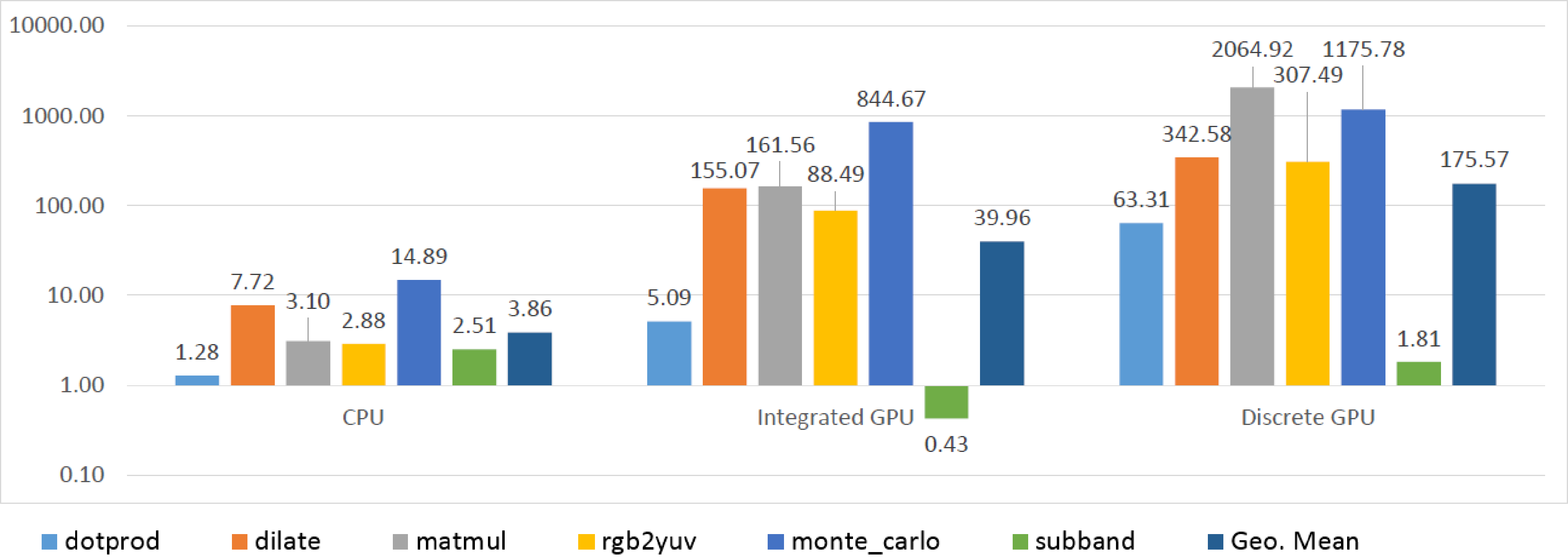
RESULTS – MATISSE C VS MATLAB



[1] A. Prasad, J. Anantpur, and R. Govindarajan, "Automatic compilation of MATLAB programs for synergistic execution on heterogeneous processors," in *ACM Sigplan Notices*, 2011, vol. 46, pp. 152–163.

RESULTS – KERNEL TIME

- Same computer, Kernel time **only** (no data transfers, no C segments)



MATLAB GPU APIS

- MathWorks Parallel Computing Toolbox:
  - CUDA API for MATLAB
  - Official, supported
- GPUmat
  - Open-source
  - CUDA API
  - Open-source, last update on 2012
- Jacket
  - CUDA or OpenCL
  - Discontinued

LIMITATIONS

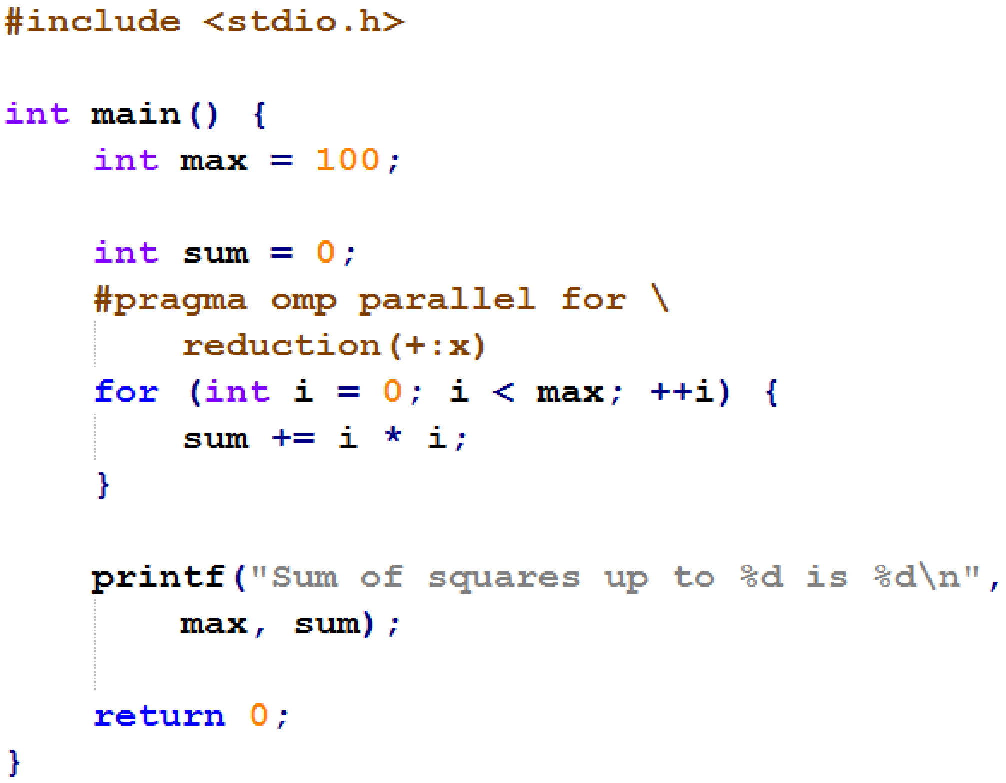
- OpenCL back-end introduced too early in the tool-chain
  - Does not take advantage of current C transformations (e.g., element-wise)
  - Only a small subset of functions are supported within a parallel block
- Odroid performance is poor

MATMUL

- Idiomatic: A = B * C;
- Simple and slow, three nested loops
- Fine-tuned with directives: separate file

OPENMP

- OpenMP: Standard for C, C++ and FORTRAN.
- Very CPU-centric.
- Code is annotated with directives.
- Compilers automatically generate the code to launch threads.



```
#include <stdio.h>

int main() {
    int max = 100;

    int sum = 0;
    #pragma omp parallel for \
        reduction(+:x)
    for (int i = 0; i < max; ++i) {
        sum += i * i;
    }

    printf("Sum of squares up to %d is %d\n",
        max, sum);

    return 0;
}
```

HOW LONG DOES MATLAB TAKE (EXAMPLE)

- Monte Carlo Option Pricing:
  - MATLAB: For 100 iterations, 12 seconds
  - MATLAB: For 1000 iterations, 113 seconds
  - MATISSE C: For 10000 iterations, takes 24 seconds
  - MATISSE OpenCL: For 10000 iterations, takes 0.02 seconds