Halide: A Language and Compiler for Optimizing Parallelism, Locality, and Recomputation in Image Processing Pipelines, *PLDI 2013*

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Outline

- Motivation:
 - Why Halide?
 - What is Halide?
 - The Halide DSL
- Implementation:
 - Scheduling Image Processing Pipelines
 - Compiling Scheduled Pipelines
 - Autotuning Pipeline Schedules
- Results
- Analysis

Motivation

We are surrounded by computational cameras

Image processing pipelines are everywhere!

- Capturing, analyzing, mining, rendering visual information
- Applications : Instagram, Adobe, etc.

⇒ Demand extremely high performance to cope with high rising resolution, frame rate, and complexity of algorithms

Motivation

Example : 3x3 blur

```
void box_filter_3x3(const Image &in, Image &blury) {
   Image blurx(in.width(), in.height()); // allocate blurx array
   for (int y = 0; y < in.height(); y++)
     for (int x = 0; x < in.width(); x++)
        blurx(x, y) = (in(x-1, y) + in(x, y) + in(x+1, y))/3;
   for (int y = 0; y < in.height(); y++)
     for (int x = 0; x < in.width(); x++)
        blury(x, y) = (blurx(x, y-1) + blurx(x, y) + blurx(x, y+1))/3;
</pre>
```



Hand optimized C++ , x11 faster

```
void box filter 3x3(const Image &in, Image &blury) {
  m128i one third = mm set1 epi16(21846);
  #pragma omp parallel for
 for (int yTile = 0; yTile < in.height(); yTile += 32) {</pre>
    ___m128i a, b, c, sum, avg;
   m128i blurx[(256/8)*(32+2)]; // allocate tile blurx array
   for (int xTile = 0; xTile < in.width(); xTile += 256) {</pre>
      m128i *blurxPtr = blurx;
      for (int y = -1; y < 32+1; y++) {
        const uint16_t *inPtr = &(in[yTile+y][xTile]);
        for (int x = 0; x < 256; x += 8) {
        a = mm loadu si128(( m128i*)(inPtr-1));
        b = mm loadu si128(( m128i*)(inPtr+1));
        c = _mm_load_si128((__m128i*)(inPtr));
        sum = mm add epi16( mm add epi16(a, b), c);
         avg = _mm_mulhi_epi16(sum, one_third);
         mm store si128(blurxPtr++, avg);
         inPtr += 8;
      }}
      blurxPtr = blurx;
      for (int y = 0; y < 32; y++) {</pre>
        __m128i *outPtr = (__m128i *)(&(blury[yTile+y][xTile]));
        for (int x = 0; x < 256; x += 8) {
          a = mm \log si128(blurxPtr+(2*256)/8);
          b = _mm_load_si128(blurxPtr+256/8);
          c = mm load si128(blurxPtr++);
          sum = _mm_add_epi16(_mm_add_epi16(a, b), c);
          avg = mm mulhi epi16(sum, one third);
          _mm_store_si128(outPtr++, avg);
}}}}
```

Writing fast image processing pipelines is **hard Optimization =>** Transform program & Data Structure

Halide's **answer**?

Separate Algorithm from Schedule aka Execution Strategy

Algorithm : What is computed Schedule: Where and When it's computed

Easy for programmers to build pipelines

Simplifies algorithm code Improves modularity

Easy for programmers to specify and explore optimizations

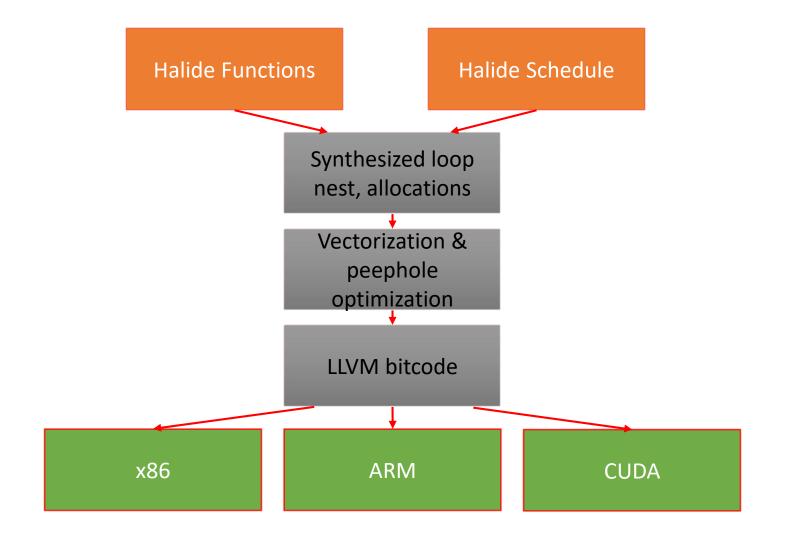
Fusion, tiling, parallelism, vectorization And **NOT BREAK THE ALGORITHM**

Easy for the compiler to generate code

What is **Halide**?

- A Domain Specific Language (DSL)
- Write high performance code easily
- Front end embedded in C++
- Compiler targets: x86/SSE, ARM v7/NEON, CUDA, Native Client, OpenCL, and Metal

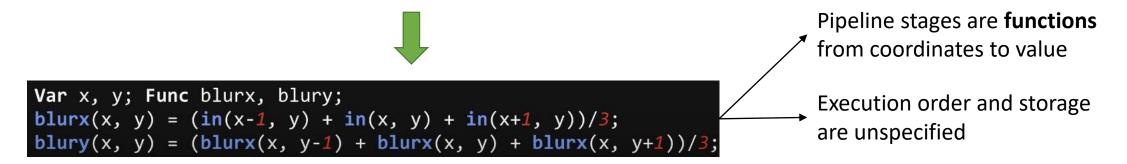
What is **Halide**?



Halide **DSL**

```
void box_filter_3x3(const Image &in, Image &blury) {
   Image blurx(in.width(), in.height()); // allocate blurx array
   for (int y = 0; y < in.height(); y++)
      for (int x = 0; x < in.width(); x++)
      blurx(x, y) = (in(x-1, y) + in(x, y) + in(x+1, y))/3;
   for (int y = 0; y < in.height(); y++)
      for (int x = 0; x < in.width(); x++)
        blury(x, y) = (blurx(x, y-1) + blurx(x, y) + blurx(x, y+1))/3;
}</pre>
```

Describe image processing pipelines in a simple functional style

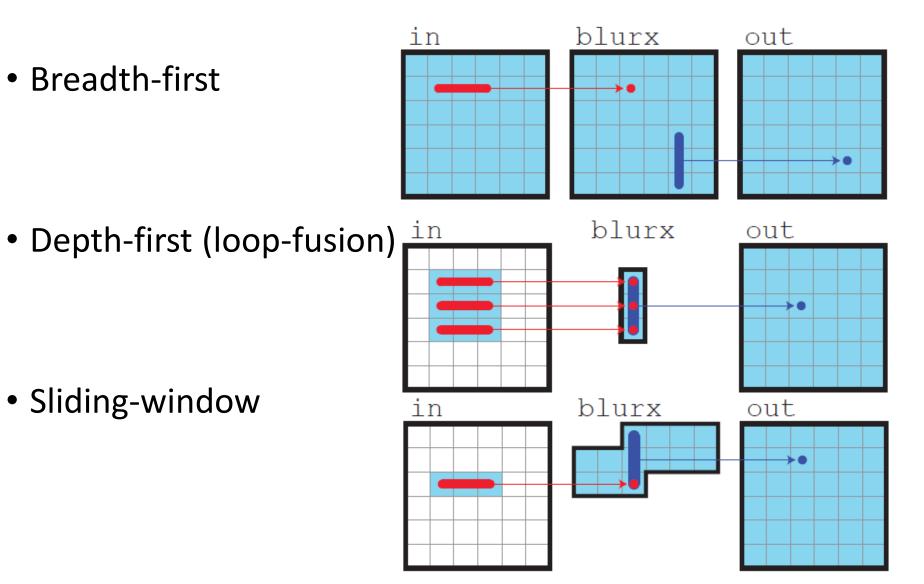


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Schedule Space

• Breadth-first



• Sliding-window

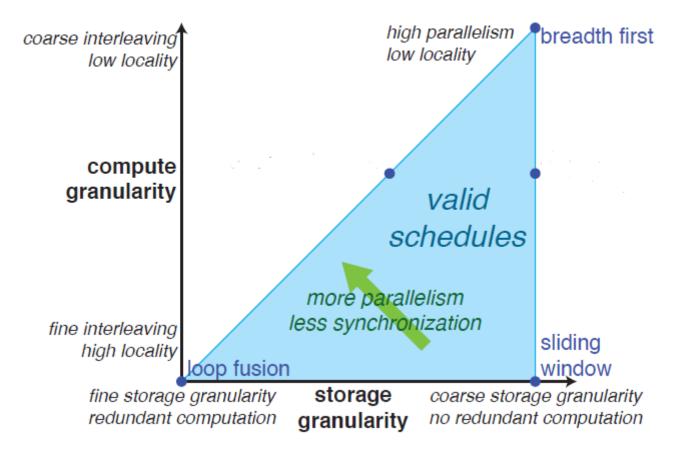
Defining a schedule

• Domain Order: Specifies order of nested iterations

```
order(y, x) =>
for y in Y_MIN ... Y_MAX:
  for x in X_MIN ... X_MAX:
```

- Call Schedule:
 - Compute granularity: Where to compute?
 - Storage granularity: How long to store?

Compute and Storage Granularity



Compute granularity <= Storage granularity Can't compute more than available storage !!

Domain Order

- Reorder: order(y, x) to order(x, y)
- Tiling: split(x, 8) -> order(tx, x)
- Vectorize: order(tx, y, x).vectorize(x)
- Parallelize: order(tx, y, x).parallel(tx)
- Strict order: order(tx, y, x).sequential(y)

Call Schedule

```
Sliding-window: blurx: store @ out.x<sub>0</sub> , compute @ out.y<sub>1</sub>
par for out.y0 in 0 ... out.y.extent/4
for out.x0 in 0 ... out.x.extent/4
alloc blurx[blurx.x.extent][blurx.y.extent]
for out.y1 in 0 ... 4
// compute blurx
vec for out.x1 in 0 ... 4
// compute out(4*x0 + x1, 4*y0 + y1)
```

Code-generation

- 1. Representation in Halide-IR
- 2. Optimizations
 - 1. Storage Folding (reduces storage granularity)
 - 2. Sliding-Window Detection (increases storage granularity)
- 3. Back-end Code-gen
 - Lower to LLVM-IR
 - GPU Code-gen
 - Loop extents must respect thread and block limitations
 - Handle data movement between host and GPU
 - Automating code-gen greatly improves programmer productivity!

Auto-tuning

- State-space explosion!
 - len(states(LaplacianFilters)) > 10^{720}
- Stochastic state-space exploration
 - Start with reasonable initial state.
 - Mutate schedule to see if mutation is better
 - Petabricks Autotuner
- Technique applied to other domains
 - ASTRA: Exploiting Predictability to Optimize Deep Learning [ASPLOS '19]

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Results

- Examples use variety of algorithms and communication patterns
- Pipelines have 2-99 stages

	# functions	# stencils	graph structure
Blur	2	2	simple
Bilateral grid	7	3	moderate
Camera pipeline	32	22	complex
Local Laplacian filters	99	85	very complex
Multi-scale interpolation	49	47	complex

Results

	Halide	Expert	Speedup	Lines	Lines	Factor		
	tuned	tuned		Halide	expert	shorter		
	(ms)	(ms)						
Blur	11	13	$1.2 \times$	2	35	$18 \times$		
Bilateral grid	36	158	$4.4 \times$	34	122	$4 \times$		
Camera pipe	14	49	$3.4 \times$	123	306	$2 \times$		
Interpolate	32	54	$1.7 \times$	21	152	$7 \times$		
Local Laplacian	113	189	$1.7 \times$	52	262	$5 \times$		

CUDA

	Halide	Expert	Speedup	Lines	Lines	Factor
	tuned	tuned		Halide	expert	shorter
	(ms)	(ms)				
Bilateral grid	8.1	18	$2.3 \times$	34	370	$11 \times$
Interpolate	9.1	54*	$5.9 \times$	21	152*	7×
Local Laplacian	21	189*	$9 \times$	52	262*	$5 \times$

x86

Analysis

Strengths

- Reduced developer time
 - Local Laplacian Filters
 - 2-3 weeks for expert to hand-optimize
 - 1 day to write in Halide
- Shorter & less complex programs
- Autotuning is target specific
 - Take advantage of specific architectures (e.g. CPU vs. GPU)
- Faster programs

Weaknesses/Limitations

- Limited to rectangular image processing
- Compilation time
 - 2 hours 2 days to run autotuning
- Autotuning is target specific
 - Schedules may work poorly on different architectures
- Tuner can get stuck in local minima
 - Requires restart with new random initialization