Neon: A Domain-Specific Programming Language for Image Processing

Brian Guenter[1] Diego Nehab[1, 2]
[1]Microsoft Research [2]IMPA

Abstract

Neon is a high-level domain-specific programming language for writing efficient image processing programs which can run on either the CPU or the GPU. End users write Neon programs in a C# programming environment. When the Neon program is executed, our optimizing code generator outputs human-readable source files for either the CPU or GPU. These source files are then added to the user source tree, compiled and executed. When targeting CPUs, the Neon compiler automatically generates highly optimized, multithreaded, vectorized code for processors supporting the SSE instruction set. For GPU applications, the compiler generates HLSL pixel shaders and the required Direct3D 10 setup code to sequence shader passes. In both cases, the performance of Neon programs rivals of other widely used general purpose image processing systems such as Apple Core Image and Adobe Pixel Bender. In particular, the performance of Neon programs running on the CPU is closer to GPU performance than might be expected from the peak floating-point performance of each architecture.

Keywords: image processing, image processing languages, domain specific languages

1 Introduction

Image processing is becoming increasingly important as digital still and video cameras decline in price and increase in capability. This declining cost has led to an enormous increase in the number of cameras worldwide and to an explosion of video and still content. The value of captured images is greatly enhanced by image processing: computer vision algorithms can identify friends and relatives to simplify video and image indexing, multiple still images can be stitched together into high resolution panoramas, photo manipulation can enhance the color saturation and sharpness of images etc. Often, the processing must be done in real time: a task which may exceed the capabilities of today's fastest computers. Even for off-line tasks, increasing the speed of image processing operations is essential to keep up with the rapidly expanding amount of content.

Modern computers have architectural features which can process images rapidly: vector instructions, multicore CPUs, and dedicated GPUs. On Intel Core i7 processors, for example, multithreading and vectorization can often increase speed by close to 16 times compared to scalar, single-threaded code. Next generation CPUs will double the width of vector operations for an additional $2\times$ performance boost [Larsson and Palmer 2009]. Even greater speed improvements are possible by moving image processing tasks to the GPU.

Unfortunately, properly using these features is not easy. For example, the SSE instruction set is available to high-level programming languages in the form of low-level intrinsics that are similar to assembly language. Furthermore, achieving peak performance on CPUs requires careful considerations of data layout and access patterns [Int 2008]. Similarly, programming for GPUs generally requires knowledge of shading languages (such as HLSL or GLSL) as well as complex graphics APIs (such as Direct3D and OpenGL). Programmers must write a substantial amount of setup code to put the GPU in the correct state and to sequence multiple rendering passes properly. In summary, in either type of architecture, writing programs that achieve the highest performance is tedious, error prone, and requires expert knowledge of low-level architectural details. Maintaining a code-base of highly optimized routines can quickly become an intractable problem, especially when many different architectures are targeted.

Neon is a new domain-specific image processing language that allows any programmer to produce image processing routines that achieve the highest levels of image processing performance, without ever worrying about the details of vectorization or multithreading. Neon programs compile natively to the CPU and the GPU, can be embedded in any application, and often outperform hand-optimized code.

2 Related Work

In contrast to hand-coded image processing libraries (such as [Int 2009]), which operate through a series of independent subroutine calls, Neon performs global analysis of a complete image-processing program to generate a single highly optimized procedure. This has several advantages: first, the programmer is not constrained by the coarse granularity of available subroutines. For example, consider a routine that converts from the RGB color space to CIE YIQ. Such a routine may take R, G, and B channels as input and return the resulting Y, I, and Q channels. If the client algorithm only needs the Y channel, then the work performed computing the I and Q channels is wasted. Second, image processing libraries process data in a sequence of independent function calls, each of which reads and writes an intermediate image, or a small block of an image. If many operations are cascaded, this leads to many unnecessary reads and writes, which can be costly even when blocking is used to keep these intermediate values in first or second-level cache. By doing a global analysis over an entire sequence of operations, the Neon compiler can frequently generate code which keeps intermediate results in CPU or GPU registers. This dramatically reduces memory traffic and therefore improves performance.

Another approach to developing image processing applications is to use one of many array programming languages. These include APL as well as the more popular and modern Matlab and IDL. The generality of these programming languages make it difficult to generate efficient multithreaded vectorized code on the CPU, and even harder to target GPUs. Programmers soon realize that high-performance is only obtainable from predefined library functions, which leads problems akin to the use of image processing libraries.

Programming environments that are specific to the domain of image processing have been commercially available for some time. Two of the most widely used are Apple's Core Image [App 2008] and Adobe's Pixel Bender [Ado 2009]. Whereas Core Image is tied to the Mac OS X platform, Pixel Bender is embedded in Adobe applications, such as Photoshop, After Effects, or Flash Player. In contrast, the Neon compiler outputs human-readable C++ and HLSL programs that can be embedded in any application and run in any platform[1].

Core Image and Pixel Bender follow the strategy of [Shantzis 1994]: the output image is defined by a graph that specifies sequences of operations (also called *filters*, *kernels*, or *effects*) to be

[1]Porting our Direct3D 10 back end to OpenGL would take a few days.

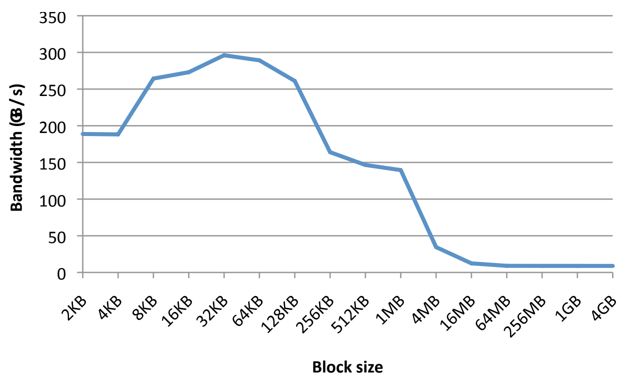


Figure 1: *Cache memory bandwidth of a 2.93 GHz Core i7 940, measured with SiSoft Sandra 2010. For small working sets the bandwidth is significantly higher than the main memory bandwidth on high-end graphics cards.*

applied to a set of inputs. At run-time, rendering is performed on demand. Conceptually, the system traverses the graph backwards and only performs the operations that are necessary for the computation of each output pixel. Both Core Image's and Pixel Bender's run-times can analyze the structure of effect graphs and eliminate unnecessary intermediate results, although the extent to which this analysis is performed in practice is unclear from publicly available documents.

The Core Image and Pixel Bender programming languages are ostensibly based on the OpenGL Shading Language, but may fallback to execution on the CPU when needed. In this case, both systems resort to emulation (which may or may not be *jitted*). This bias towards GPUs leads to significant performance losses when code runs on a CPU. Even the fastest CPU implementations of pixel shading (see WARP, for example [Glaister 2008]) carry too much overhead simulating GPU behavior (rasterization, pixel formats, etc) to be competitive in general image processing tasks.

Neon was designed to satisfy three goals: make the language as general purpose as practical, hide all low-level architectural details from the user, and generate the most efficient code possible. The decision to emphasize efficient code generation, in particular, places strong constraints on generality. The current implementation of Neon requires all images to be of the same size, in the same coordinate frame, with all pixels at integer locations. This simplification has allowed us to generate exceptionally efficient code for both the CPU and GPU but still gives the language enough generality so that it can perform the most common, and important, image processing functions used for picture and video editing.

Neon programs are written in a higher-level language that was not designed for GPUs exclusively. Our CPU and GPU back ends generate native code for each architecture, using the best data layouts in each case. The result is much better performance when running on CPUs, and no compromise when running on GPUs (see tables 5, 6, and 7).

3 Architectural Characteristics

Determining whether to perform imaging operations on the CPU or the GPU, and how to optimize code for those operations, requires an understanding of the very different architectural characteristics of these two devices. One must also consider the nature of typical image processing operations, which tend to have regular memory access patterns but a low arithmetic to memory-access ratio (we will refer to this as FLOPS/IO).

Table 1: *Comparison of memory bandwidth of a Core i7 CPU to low and high end GPUs. The column labeled main memory shows the bandwidth from the GPU processor to the graphics card main memory, and from the CPU to the CPU main memory. The next two columns show the speed of transferring data from the CPU to the GPU and back. Measured with SiSoft Sandra 2010.*

Processor	Main memory	CPU to GPU	GPU to CPU
HD 4850	29.2 GB/s	4.24 GB/s	351 MB/s
HD 5870	114 GB/s	4.26 GB/s	870 MB/s
470 GTX	103 GB/s	2.42 GB/s	5.28 GB/s
Core i7 940	18 GB/s	N/A	N/A

In figure 1 and table 1, we can see how different these two architectures are. For an application with a working set size of 128KB or less, the cache bandwidth of a 2.93GHz Core i7 940 CPU[2] is over 250GB/s. Even for a working set size as large as 1MB, the cache bandwidth is still almost 150GB/s. Memory latency, shown in figure 2, is also very low: 1.4ns (4 clock cycles) for accesses within a 16KB range, and less than 5ns for accesses within a 256KB range.

The Sandra benchmarks only measure main memory bandwidth for graphics cards so we can't directly compare cache performance between CPUs and GPUs. Referring to table 1 we can see the bandwidth from main memory to the CPU is 18GB/s for the Core i7. The ATI Radeon HD 4850, a low-cost graphics card[3], has slightly better performance, achieving 29GB/s bandwidth to internal GPU memory. GPU to CPU transfers are especially slow, at about 350MB/s. The far more powerful ATI Radeon HD 5870[4] has much higher internal memory bandwidth (114GB/s) and faster, but still slow, GPU to CPU bandwidth[5]. The NVIDIA 470 GTX GPU has high internal bandwidth, 103GB/s, and, surprisingly, higher GPU to CPU than CPU to GPU bandwidth. But even with this higher bandwidth, the round-trip overhead makes the GPU less attractive for processing tasks that require image data to be sent to the GPU and returned to the CPU.

From this, we can expect GPUs to perform well on workloads that:

- do not require round-trip data transfers to CPU main memory;
- have a high arithmetic to memory-access ratio;
- have regular memory access patterns, preferably streaming the data through the GPU once or at most a few times.

CPUs have much lower raw floating-point performance compared to GPUs, but have much larger caches, with very high bandwidth; keeping computation in cache as much as possible can yield large performance gains, especially for workloads that have low computation to memory-access ratio or irregular memory access patterns.

4 Architecture of the Neon System

Neon is a domain specific programming language embedded in the C# programming language. Neon programs are written in C#; operator overloading and custom class types and constructors are used to define the semantics of the Neon language[6]. We chose C# as the host language for Neon because it is a modern language, with labor

[2]$550 as of April 2010

[3]$110 as of April 2010.

[4]$400 as of April 2010.

[5]Incidentally, the PCIe bus has symmetrical up and down bandwidth so these low numbers are probably due to driver inefficiencies.

[6]Other languages supporting operator overloading could be used instead.

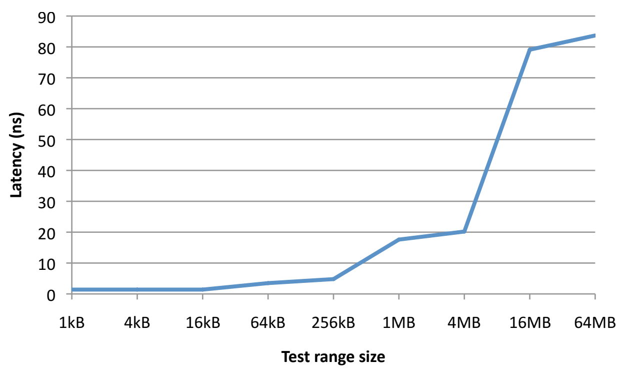


Figure 2: *Memory latency for a 2.93 GHz Core i7 940, for various ranges of memory access. Measured with SiSoft Sandra 2010.*

Table 2: *Comparison of floating point performance of Core i7 CPU to low and high end GPUs. GPU FLOPS is the manufacturer's specification. CPU FLOPS is measured Whetstone iSSE3 GFLOPS. The column which lists speed in Mpixels/sec uses a Sandra benchmark which allows for direct comparison of GPGPU and CPU speeds. Measured with SiSoft Sandra 2010.*

Processor	FLOPS	MPixels/s
HD 4850	1 TFLOPS	286
HD 5870 (850MHz)	2.72 TFLOPS	926
470 GTX	N/A	1210
Core i7 940 (2.93GHz)	63 GFLOPS	124

and complexity reducing features such as automatic garbage collection. In addition, excellent C# programming environments, which make it easier to write and debug Neon programs, are available on both proprietary and open-source platforms.

There are two components to the Neon system. The first is the Neon language itself, along with the Neon compiler. The second component is an interactive test framework, which allows Neon programs to be interactively tested immediately after they are compiled.

The process of getting from a Neon input program to a final executable is illustrated in figure 3.

Neon programs are implicitly pixel parallel; the order of computation of pixels is left unspecified to allow the code generator maximum flexibility to exploit parallelism on the target architecture. There is an implicit current pixel location at which all operations are performed. User wishing to access pixels other than the current pixel location use the *offset* function, which returns the pixel at position $(current_x + offset_x, current_y + offset_y)$. Convolution, rather than being a built-in primitive operator, is performed by using a series of calls to the offset function.

A simple Neon program, which computes a Laplacian of Gaussian high-pass filter, is shown below. It takes one input image and produces one output image. The bit width of input and output channels must be defined; currently the supported bit widths are 8-bit unsigned, 16-bit unsigned, and 32-bit float[7]. All intermediate images are 32-bit float, by default. Users can also define scalar parameters as arguments to the Neon function using the `ScalarParameterVariable` object type. Minimum, maximum, and initial values for scalar parameters can be set and these values will be displayed on the interactive test framework.

```
public static Im laplacian() {
    //Variable Declarations
    In16Bit r = variable16Bit("r");
    ScalarParameterVariable alpha = "alpha";
    alpha.setRange(0.0f, 20.0f);
    alpha.initialValue = 2.0f;
    //End Variable Declarations
    Const[,] colFilter = laplacianFilterKernel();
    Im rl = alpha * convolve(r, colFilter);
    Im result = new Im(out16Bit(rl));
    return result;
}

public static Const[,] laplacianFilterKernel() {
    return new Const[,] { { 4f, -1f }, { -1f, 0f } };
} //non-negative quadrant of lapacian filter kernel
```

[7]8,16, and 32-bit for GPU code; 16 and 32-bit for CPU code.

In the Laplacian code example, the function convolve[8] is a Neon library function, but it is not a primitive operator; it is itself written in the Neon language.

4.1 Optimizations

Neon performs two types of optimizations: generic and target specific. Generic optimizations are done in the first optimization pass and include common subexpression elimination, algebraic simplification, and minimization of the number of intermediate images. Target specific optimizations depend on the architectural characteristics of the target processor and include data packing and unpacking to maximize cache coherence, restructuring convolutions to minimize I/O, and precomputing offset indices.

Before an expression is created, its hash code is used to see if it already exists. If it does, the existing expression is used, otherwise a new expression is created. Commutative operators, such as $+$ and $*$ test both orderings of their arguments.

Algebraic simplification is performed as the expression graph is being created. This approach is more efficient than performing graph rewriting after the entire expression graph has been created. It is also powerful enough to handle the most common and useful algebraic simplifications. For example, the constructor for the $*$ operator[9] performs the following symbolic algebraic simplifications:

$$\begin{array}{lllll} a*1 & \to & a & a*-1 & \to & -a \\ a*0 & \to & 0 & c_0*c_1 & \to & \text{Const}(c_0*c_1) \end{array}$$

where a is a variable argument to the $*$ operator, c_0, c_1 are constant arguments to the $*$ operator, and Constant() is the constructor for the Constant class, which creates a new node representing a constant value. The algebraic simplifications currently performed for all operators are:

$$\begin{array}{llllll} a*1 & \to & a & a*-1 & \to & -a \\ a*0 & \to & 0 & a\pm 0 & \to & a \\ a/a & \to & 1 & a/(-1) & \to & -a \\ a-a & \to & 0 & f(c_0) & \to & \text{Const}(f(c_0)) \\ c_0*c_1 & \to & \text{Const}(c_0*c_1) & c_0\pm c_1 & \to & \text{Const}(c_0\pm c_1) \\ c_0/c_1 & \to & \text{Const}(c_0/c_1) & & & \end{array}$$

4.2 Minimizing the Number of Intermediate Images

The most important optimization Neon performs is minimizing the number of intermediate images created. Intermediate images only

[8]See the supplemental materials for source code.
[9]See supplemental materials for source code.

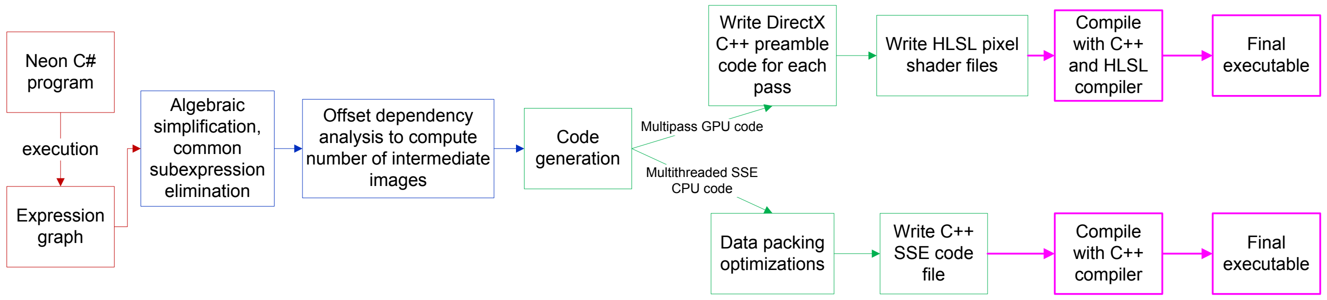

Neon C# program
execution
Expression graph
Algebraic simplification, common subexpression elimination
Offset dependency analysis to compute number of intermediate images
Code generation
Multipass GPU code
Multithreaded SSE CPU code
Write DirectX C++ preamble code for each pass
Write HLSL pixel shader files
Compile with C++ and HLSL compiler
Final executable
Data packing optimizations
Write C++ SSE code file
Compile with C++ compiler
Final executable

Figure 3: *Processing flow of a Neon program*

need to be computed when a node has two or more `Offset` node ancestors which have different offset values. To see why this is true, look at the following code fragment

```
Input16Bit r;

Im temp = r*r;
Im result = offset(temp,0,1)+offset(temp,0,2);
```

which might naively be translated to

```
foreach(pixel in the image) {
  temp[i,j] = r[i,j]*r[i,j];
  result[i,j] = temp[i+1,j] + temp[i+2,j];
}
```

This code is not correct because the order in which pixel values are computed is not specified in Neon. Suppose pixels are computed from the bottom of the image to the top. Then, at the point where we want to assign a value to `result[i,j]`, the values `temp[i+1,j+0]`, and `temp[i+2,j+0]` will not have been computed yet. It would be possible to recursively expand the subgraph for each offset, resulting in code like this:

```
foreach(pixel in the image){
  result[i,j] = r[i+1,j]*r[i+1,j]
    + r[i+2,j]*r[i+2,j];
}
```

but this repeats all of the subgraph computation as many times as there are offsets[10]. Even worse, if offsets are nested the computation increases exponentially with the depth of the nesting.

Instead of replicating computation, the Neon graph optimizer computes the minimal number of intermediate images necessary to eliminate all offset conflicts, and inserts `Intermediate` nodes into the graph where necessary, as in figure 4. Algorithm 1 shows how to find intermediate nodes[11]. The function `findIntermediates` is called with a list of all roots of the graph. In the final code generation stage, each `Intermediate` node will cause code to be created that writes an intermediate image.

4.3 Target Specific Optimizations

The compiler performs many target specific optimizations. We will just mention a few here that each improved performance fairly significantly. For CPU code generation we use OpenMP parallel constructs to parallize computation across scanlines. Image processing is non-blocked, and images are stored in planar, rather than interleaved, form because this maps much better to the SSE instruction set. Intermediate image nodes cause multiple processing loops, called phases, to be generated. Each loop may have operations on an arbitrary number of images so long as they do not have dependencies on intermediate images which have not yet been computed in a previous phase.

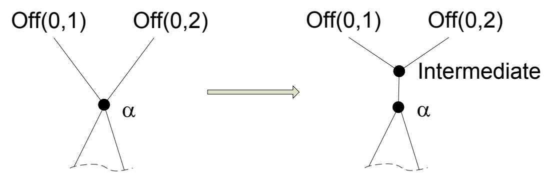


Figure 4: *When node α has two or more conflicting offset nodes as ancestors, an intermediate image must be created. Otherwise, all the computation of the subgraph below α would be repeated for each ancestor of α.*

The compiler generates code to up convert low bit resolution data on-the-fly as it is being read read and to downconvert it on writes. This eliminates the need to create temporary images solely for the purpose of storing data upconverted from low to high bit resolution, for example creating a temporary 32-bit image to store 8-bit input data that has been converted to 32-bit data.

If multiple offsets are present in any one phase, the compiler creates code to do reads and writes of multiple pixels in a batch, unpacking data on the fly.

Small separable convolution kernels are transformed into non-separable kernels; the extra computation is more than outweighed by the reduction in memory data transfer.

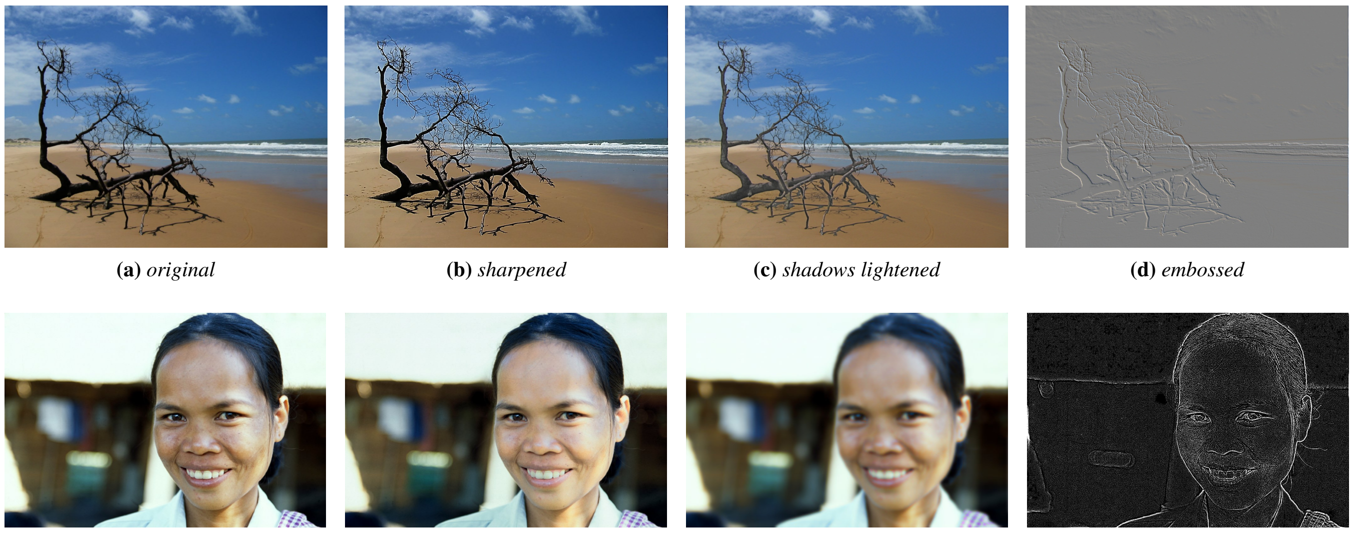
In DirectX10 integer indexing is supported for the `Load` method for indices between -7 and 8. The compiler automatically generates precomputed integer indices for offsets that lie within this data range.

5 Results

In section 5.1, we describe the benchmarks and the benchmark setup. In section 5.2, we compare Neon code executing on the GPU to Neon code executing on the CPU, and draw conclusions about the FLOPS/IO ratio necessary to get peak performance. In section 5.3, we compare Neon code to three commercial competitive systems: Adobe's Pixel Bender, Apple's Core Image, and Microsoft's WARP. In some sense, this is not an apple to apple com-

[10]Depending on the relative cost of I/O to computation, it may be faster to recompute than to write a temporary intermediate image. This is only likely to be true when the number of offsets is small, say 2 or 3; our experience has been that this is quite uncommon in real world image processing algorithms, so by default Neon always creates intermediates images.

[11]The actual code used in the compiler is slightly more complex; it coalesces non-conflicting offsets into a single offset.



(a) *original* **(b)** *sharpened* **(c)** *shadows lightened* **(d)** *embossed*

(e) *original* **(f)** *spectral weighting* **(g)** *separable blur* **(h)** *Laplacian*

Figure 5: *Benchmark image processing examples. (a) Original image. (b) Unsharp masking with 5×5 separable Gaussian low-pass filter. (c) Local contrast control with shadows enhanced. (d) Embossing operator. (e) Original image. (f) Spectral weighting with high R channel weight. (g) 23x23 separable low-pass Gaussian filter. (d) 3x3 Laplacian-of-Gaussian filter.*

Algorithm 1 Finding the minimum number of intermediate images.

```
findIntermediates(nodeList, intermediates)
offsets: Dictionary<node, Offset>
visited: Dictionary<node, bool>

while nodeList not empty {
  if (node is Offset) offsets[node] = node
  foreach (child of node) {
    if (offsets[child] == NULL)
      offsets[child] = offsets[node]
    else if (offsets[child] != offsets[node])
      intermediates[child] = true
    visited[child] = true
  }
  nodeList = visited.Keys
}
```

parison, since all three commercial systems are designed to perform many operations that Neon does not. Nevertheless, these are the most widely available systems for writing image processing programs and the core operations provided by Neon are used in virtually every image processing application. It is therefore relevant to find out what advantage can be gained in terms of performance by restricting the domain of the language to a subset that encompasses many of the most frequently used operations, but that excludes operations such as general scales, warps, or resampling in general.

As described in section 2, Pixel Bender allows users to create custom image processing effects for several Adobe products. It does not generate code that can be linked into a user's application. Core Image is an image processing system which is supported only on Mac OS X. Core Image subroutines can be called directly from end user code. WARP is Microsoft's software implementation of the entire Direct3D pipeline. It includes a jitter that recompiles HLSL code, written for the GPU, into multithreaded SSE code which then runs on the CPU. Its primary use is to allow DirectX programs to run on computers which do not have hardware GPU support for the latest DirectX features.

5.1 Benchmarking Conditions

Six real-world image processing benchmarks were written in Neon, Core Image, and Pixel Bender. These were tested on CPU and GPU processors:

- *unsharp* (figure 5b), uses color space conversion from RGB to YIQ, and separable filtering with a 5×5 Gaussian to increase the apparent sharpness of an image;
- *contrast* (figure 5c) uses the algorithm of [Moroney 2000], involving separable low-pass filtering and conditional operators to selectively brighten shadows or tone-down highlights;
- *emboss* (figure 5d) subtracts an offset version of the image from itself to create a pseudo-3D embossed effect;
- *spectral* (figure 5f) transforms from RGB to YIQ color space, but gives the user control over the weights applied to R, G, and B when computing the Y. It then converts back to RGB using the standard weights.
- *separable* (figure 5g), uses a 23×23 separable low-pass Gaussian filter to blur the image;
- *Laplacian* (figure 5h), uses a 3×3 Laplacian of Gaussian filter kernel to compute the edges of an image;
- *repeated x* (not shown) repeatedly converts from RGB to YIQ and back, where x is the number of repetitions.

All the benchmarks are fairly standard image processing operations, except for *repeated x*. This synthetic benchmark is used to generate a sequence of computations of increasing FLOPS/IO to measure the relative change in performance between the GPU and CPU as a function of the FLOPS/IO ratio.

The CPU back-end code generator currently only supports 16 and 32-bit per channel for input and output, while the GPU supports 8,

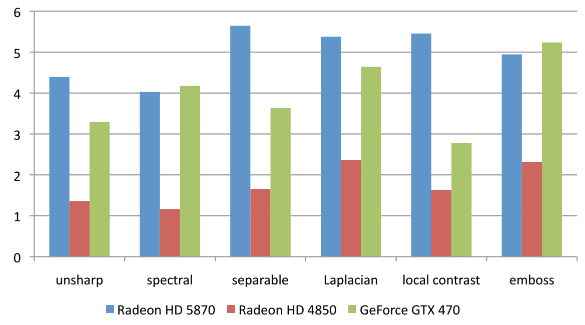


Figure 6: *Ratio of speed of Neon GPU code vs. Neon CPU code: 16bit RGB input and output.*

16, and 32-bit I/O. When comparing the relative performance of the CPU and GPU code, we use 16 bit I/O.

All intermediate images are 32-bit floating-point for both the GPU and CPU codes. GPU benchmarks were run on the ATI Radeon HD 5870, ATI Radeon HD 4850, and NVIDIA GeForce 470 GTX. CPU benchmarks for Core Image comparisons were run on an iMac 27", with a Core i7 860 @ 2.8GHz, 8GB RAM DDR3 @ 1067MHz, with an ATI Radeon HD 4850 with 512MB of RAM. All other CPU benchmarks were run on a Dell Studio XPS workstation with 12GB of RAM DDR3 @ 1067Mhz and a 2.93 GHz Intel Core i7 940. All four cores were used.

Because of differences in the GPU and CPU architectures, the number of floating-point operations per pixel is not exactly equal for each benchmark, as can be seen in table 4. The CPU code has to convert from 16-bit to 32-bit data on input and output; for very small programs this extra overhead causes the CPU programs to have a higher FLOPS/pixel count than the GPU. On the GPU, this conversion is performed automatically by the hardware. This difference in computation is generally quite small relative to the total work done in the benchmark.

GPU timings include *only* the cost of doing the computation on the GPU, not the significant round-trip cost of transferring the image from CPU main memory to the GPU and back. For the GPU with the fastest transfer rates, the NVIDIA GeForce 470 GTX, the round trip overhead reduces the maximum possible frame rate to no more than 350fps, more than an order of magnitude slower than this processor is capable of computing results. For the GPU with the second fastest transfer rates, the AMD Radeon HD 5870, the maximum possible frame rate is only 153fps.

5.2 Comparison of Neon GPU and CPU Code

In this section, we compare Neon code executing on the GPU to Neon code executing on the CPU. The benchmarks can be roughly divided into two groups: low FLOPS/IO, which includes *Laplacian*, *spectral*, and *emboss*, and high FLOPS/IO, which includes *unsharp*, *separable*, and *contrast*.

Table 3: *Speed, in GPixels/s, for image processing benchmarks. 5870 and 4850 are both ATI Radeon HD GPUs. Core i7 is CPU. Image size 1024x768, input and output images 16bit RGBA.*

Operation	HD 5870	HD 4850	470 GTX	Core i7 940
unsharp	1.66	.51	1.24	.377
spectral	4.46	1.29	4.6	1.12
separable	1.02	.301	.662	.18
Laplacian	4.39	1.93	3.79	.817
contrast	1.28	.385	.897	.235
emboss	4.39	2.06	4.65	.887

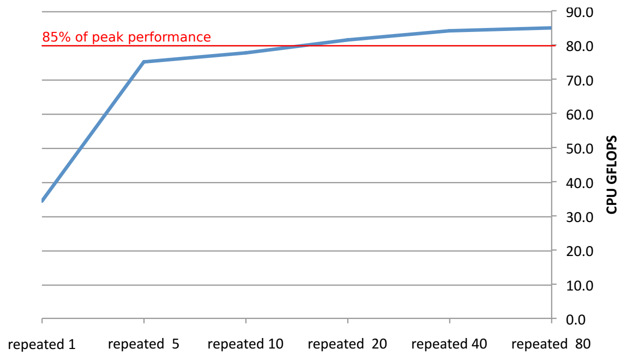


Figure 7: *CPU speed, in GFLOPS, measured with the* ***repeated*** *synthetic benchmark. More repetitions increases the FLOPS/IO ratio. Non-synthetic benchmarks have FLOPS/IO ratio roughly equal to repeated 1.*

For the CPU code, we see from table 3 that benchmarks with low computation per pixel achieve performance which is close to being memory bandwidth limited. The *Laplacian* benchmark has the lowest operations count, 10 FLOPS, reads a single 16-bit input and writes three 16-bit outputs. This uses 17.6GB/s of main memory bandwidth, which is very close to the maximum achievable[12].

For the high-performance GPUs (Radeon HD 5870 and GeForce 470 GTX) performance ranges from 3 to 5.5 times faster than the CPU. The low performance GPU (Radeon HD 4850) ranges from 1.2 to 2.4 times as fast as the CPU.

The benchmarks *Laplacian, spectral* and *emboss* do relatively little computation and have the lowest relative GPU performance. Their framerate on the GPU is nearly identical even though *Laplacian* does roughly one third the computation of *spectral*; a strong indication that these benchmarks are limited either by GPU I/O bandwidth or by driver overhead.

The benchmark *repeated* x, used for the plots in figures 7, 8, and 9, lets us examine how computational speed changes as a function of the FLOPS/IO ratio. As the number x of repetitions increases, the FLOPS/IO ratio increases. We ran benchmarks with up to 80 repetitions, which perform about 2200 arithmetic operations per pixel

[12]Recall from table 1 that main memory bandwidth on the CPU is 18 GB per second.

Table 4: *Comparison between the GPU and CPU: floating point operations per pixel and effective FLOP rate. Because of extra indexing calculations for the GPU code sometimes the FLOPS/pixel is higher than for the CPU. Conversely, because the CPU has to convert from 16-bit to 32-bit some simple programs have more FLOPS/pixel than for the GPU.*

Operation	Core i7 940		HD 5870	
	FLOPS/pixel	GFLOPS	FLOPS/pixel	GFLOPS
unsharp	70	26.4	90	149
spectral	31	35	31	138
separable	102	18.4	115	118
Laplacian	25	20.4	13	57
contrast	89	20.9	114	146
emboss	22	19.5	22	96

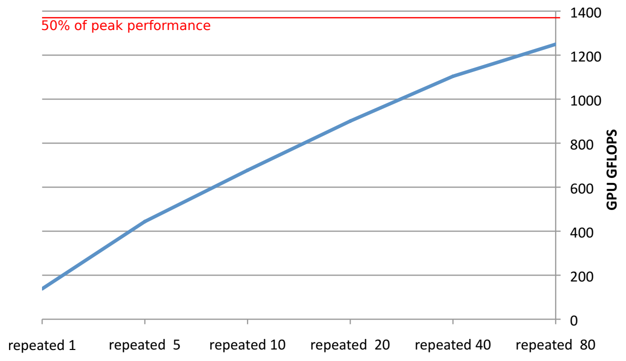


Figure 8: *HD 5870 GPU speed, in GFLOPS, measured with the* ***repeated*** *synthetic benchmark. More repetitions increases the FLOPS/IO ratio. Non-synthetic benchmarks have FLOPS/IO ratio roughly equal to repeated 1.*

of IO, far higher than any of the standard image processing benchmarks.

On the Core i7 architecture, it is possible, under ideal conditions, to execute one multiply-add per clock cycle. The processor has four cores and there are four 32-bit floating-point words in each SSE word. The peak possible 32-bit floating-point performance therefore is: clock-speed$\times 2 \times 4 \times 4$. For the benchmark machine, this results in 93.7GFLOPS. As can be seen in figure 7, the CPU floating-point performance increases rapidly between *repeated* 1 and *repeated* 5, and then levels off at close to the peak possible performance: *repeated* 20, 40 and 80 achieve 87%, 90%, and 91% of peak, respectively. Unfortunately, the FLOPS/IO ratio of the more realistic benchmarks are roughly equal to *repeated* 1, significantly less than required to achieve peak performance.

We show just one graph for the GPUs since the general trend for all three is similar. The peak advertised performance of the Radeon HD 5870 GPU is 2.72TFLOPs; the GPU never reaches this peak in our benchmarks (see figure 8), although it does approach 50% of peak theoretical performance. The slope of the graph is such that performance appears to still be increasing at 80 repetitions. This is is already an unrealistically high FLOPS/IO ratio for image processing operations, so we did not test pass this point.

In spite of the much higher peak floating-point performance of the Radeon HD 5870 GPU, the ratio of GPU to CPU speed is relatively low for realistic image processing benchmarks. Even for the *repeated* 5 benchmark, which has a significantly larger FLOPS/IO ratio than any of the benchmarks typical of real-world applications, the GPU/CPU speed ratio is only 6. For these benchmarks, the GPU/CPU speed ratio appears to be more closely related to the ratio of memory bandwidth than to the ratio of floating-point performance. This is not entirely surprising given the low FLOPS/IO nature of typical image processing operations.

5.3 Comparison between Neon, Pixel Bender, Core Image, and WARP

Neon GPU code was faster than Pixel Bender GPU code for all 6 benchmarks, by a minimum of 2.2x and a maximum of 7.8x. On three of the six benchmarks, Neon code running on the CPU outperformed Pixel Bender running on the fastest GPU. Neon CPU code was roughly two orders of magnitude faster than Pixel Bender CPU code.

On four of the six benchmarks, Neon GPU code was faster than Core Image GPU code, by a minimum of 1.4 and a maximum of

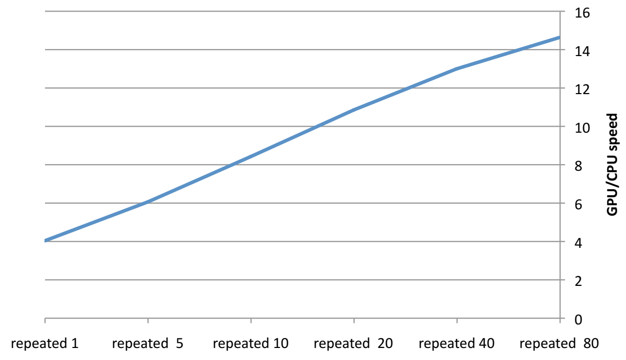


Figure 9: *Ratio of HD 5870 GPU to CPU speed, measured with the* ***repeated*** *synthetic benchmark. More repetitions increases the FLOPS/IO ratio. Non-synthetic benchmarks have FLOPS/IO ratio roughly equal to repeated 1.*

2.5. Neon CPU code is almost one order of magnitude faster than Core Image CPU code. WARP has surprisingly good performance on the CPU, by comparison to Core Image and Pixel Bender, but Neon CPU code was faster than WARP on all 6 benchmarks by a minimum of 3.8 and a maximum of 7.8.

These results are surprising in several ways. First, properly optimized CPU code can be competitive with code running on a GPU, except when the GPU is state-of-the-art. While the fastest GPUs sold today execute our benchmark image processing operations many times faster than similarly priced CPUs, the majority of computers are sold with relatively low-speed GPUs; many have integrated graphics chips with performance far lower than the lowest performance graphics card we tested. Second, the difference in speed between the GPU and CPU appears to be more closely related to the difference in memory bandwidth than to the difference in floating-point performance. For example, the peak floating-point performance of the ATI Radeon HD 5870 and the Intel Core i7 940 differ by a factor of nearly 30. But the measured GPU/CPU speed ratio for real world image processing programs written in Neon is less than 6, which is close to the memory bandwidth ratio of 5.7. Finally, Neon code running on the CPU can, at times, outperform Pixel Bender or Core Image code running on the GPU, possibly due to the overhead of the on-demand rendering paradigm employed by these systems. Neon CPU code dramatically outperforms Pixel Bender, Core Image, and WARP.

Table 5: *Comparison of Neon GPU executables vs. Adobe Pixel Bender. All speeds are in fps. Bold numbers indicate fastest times. Bold red numbers indicate Neon CPU code ran faster than Pixel Bender GPU code.*

Operation	470 GTX		HD 4850		Core i7 940	
	Neon	P B	Neon	P B	Neon	P B
unsharp	**1578**	531	**653**	282	**479**	8.8
spectral	**5875**	806	**1640**	401	**1407**	14.8
separable	**842**	380	**383**	229	**231**	5*
Laplacian	**4819**	652	**2462**	380	**1038**	10.8
contrast	**1149**	373	**489**	248	**299**	5*
emboss	**5907**	752	**2616**	342	**1127**	14.2

*The Pixel Bender tool doesn't report frame rates below about 5 fps so we had to manually estimate these frame rates.

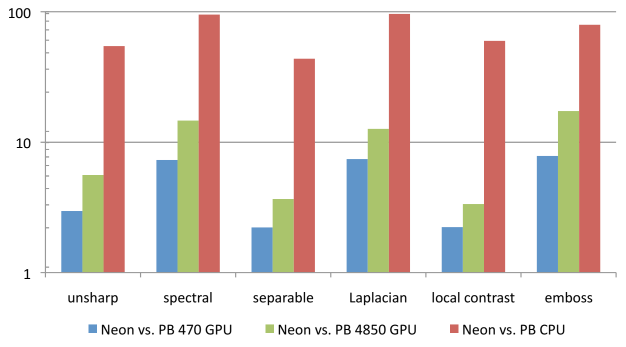


Figure 10: *Bar chart showing relative performance of Neon vs. Pixel Bender code. Vertical scale is logarithmic. 470 is NVIDIA 470 GTX, 4850 is ATI Radeon HD 4850, and CPU is Core i7 940.*

6 Conclusion

The Neon image processing language strikes a good balance between generality and speed of execution. Neon programs are easy to write, easy to understand, and hide all low level architectural details from the programmer. Many common image processing operations can be expressed entirely in the language and the resulting executables have excellent performance. For GPU executables, Neon outperforms Core Image and Pixel Bender by factors of anywhere from 1.4 to 7.8. For CPU executables, Neon outperforms Core Image by almost an order of magnitude, Pixel Bender by two orders of magnitude, and WARP by a factor of roughly 5.

References

ADOBE SYSTEMS INC. 2009. *Pixel Bender Developer's Guide*.

APPLE INC. 2008. *Core Image Programming Guide*.

GLAISTER, A. 2008. *Windows Advanced Rasterization Platform, In-Depth Guide*. Microsoft Corp.

INTEL CORP. 2008. *Intel 64 and IA-32 Architectures Optimization Reference Manual*. Order Number: 248966-017.

INTEL CORP. 2009. *Intel Integrated Performance Primitives*.

LARSSON, P., AND PALMER, E. 2009. *Image Processing Acceleration Techniques using Intel Streaming SIMD Extensions and Intel Advanced Vector Extensions*. Intel. Corp. Whitepaper.

MORONEY, N. 2000. Local color correction using non-linear masking. In *Color Imaging Conference*.

SHANTZIS, M. A. 1994. A model for efficient and flexible image computing. In *SIGGRAPH '94*, 147–154.

Table 6: *Comparison of Neon GPU executables vs. Apple Core Image. All speeds are in fps. Bold numbers indicate fastest times. Bold red numbers indicate Neon CPU code ran faster than Core Image GPU code.*

Operation	HD 4850		Core i7 860	
	Neon	C I	Neon	C I
unsharp	**653**	475	**392**	31.7
spectral	**1640**	968	**1020**	153
separable	383	**517**	**193**	28.5
Laplacian	**2462**	978	**955**	120
contrast	434	**707**	**236**	48.1
emboss	**2616**	1078	**984**	165

Table 7: *Comparison between Neon CPU native code and pixel shader emulation through Microsoft's WARP. All speeds are in fps. Bold numbers indicate fastest times.*

Operation	Core i7 940	
	Neon	WARP
unsharp	**479**	63
spectral	**1407**	180
separable	**231**	61
Laplacian	**1038**	131
contrast	**299**	59
emboss	**1127**	161