Evaluation and Exploration of Next Generation Systems for Applicability and Performance (Volodymyr Kindratenko, Guochun Shi)

1 Summary

We have ported image characterization algorithm implemented in doc2learn application to the Graphics Processing Unit (GPU) platform using both CUDA C targeting NVIDIA GPUs and OpenCL targeting NVIDIA and AMD GPU architectures. We also implemented doc2learn image analysis algorithm in C targeting microprocessor architecture. Our conclusion is that doc2learn image processing part can be accelerated up to 4 times using NVIDIA GTX 480 GPU, but 1) the speedup depends on the image size and 2) other parts of doc2lear application dominate the execution time.

2 Preliminaries

Doc2learn implements algorithms for computing *probability density functions* for text, image, and vector graphics objects embedded into PDF files. Specifically, non-parametric probability density function estimation techniques are implemented that require computing a histogram of frequencies of occurrence of all values in a particular object, e.g., image or text. The computed probability density functions (histograms) form the feature vector which can be used for measuring the similarity between pairs of images.

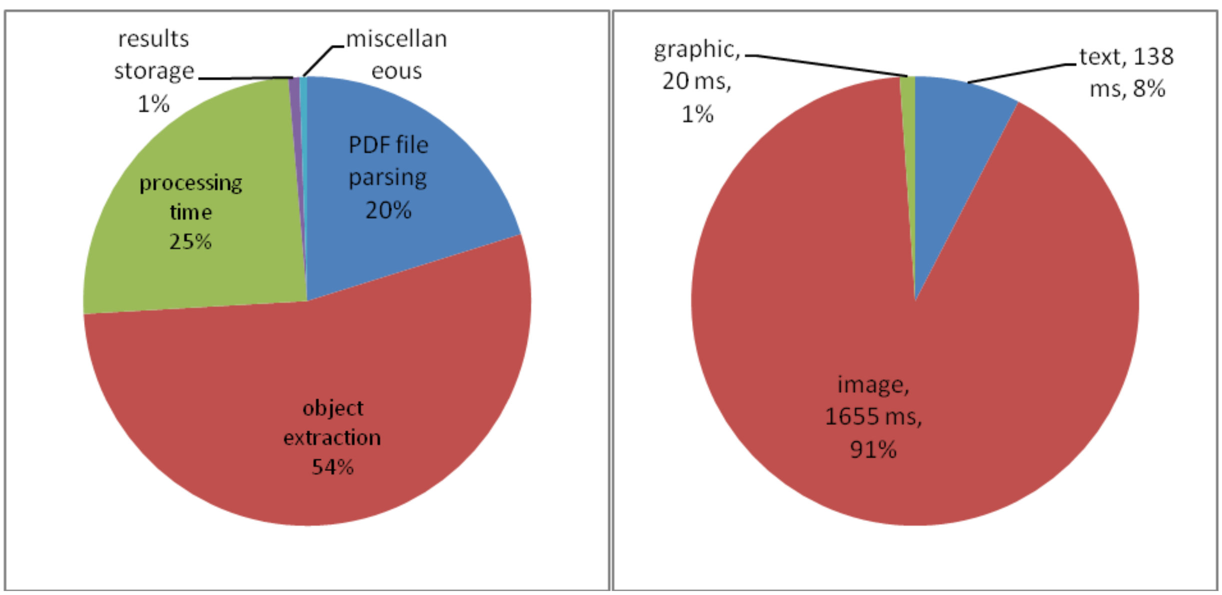


Figure 1. Doc2learn execution profile using has.PDF as an example. Pie chart on the left shows time distribution of the entire application. Pie chart on the right shows time distribution of the data processing part, which is 25% of the overall application execution time.

Application profiling of doc2learn SVN revision 760 on has.pdf file (one of test cases) reveals that about 25% of the overall time is spent on the probability density function computation (Figure 1, left) most of which is spent on the image analysis (Figure 1, right). This time distribution is typical for documents containing many images.

Doc2learn is written in Java. Java code is executed by a virtual machine that executes on top of the actual hardware (microprocessor). Java virtual machine isolates many of the performance-enhancing features of the underlying hardware, such as vector units, thus potentially not allowing to fully utilize the capabilities of modern microprocessors without explicitly programming for them. **The main goal of this study is to investigate how the execution of the probability density function computation for images can be improved on modern microprocessor architectures and GPUs.** We specifically target image analysis part of the doc2learn application because it is perceived to be the most data-intensive and time-consuming part of the computation for documents that contain either a lot of images or large-size images.

2.1 Doc2learn image characterization algorithm

Doc2learn implements a non-parametric probability density function estimation technique which is based on the computation of a histogram of frequencies of occurrence of pixels of different colors in an image. Most significant bits of red, green, and blue components (and optionally alpha channel when present) of each image pixel are used as indexes of a 3D array that holds the histogram. This algorithm is an improvement over the histogram computation algorithm used in earlier versions of doc2learn. Instead of building a histogram consisting of all color values present in the image, a highly reduced histogram is computed, resulting in a very significant (over an order of magnitude) reduction of the computation time.

Figure 2 contains the Java source code for probability density function estimation taken from the original doc2learn implementation.

```
// compute histogram for image
int pix, red, green, blue;
for (int r = 0; r < bi.getHeight(); r++ ) {
    for (int c = 0; c < bi.getWidth(); c++ ) {
         pix = bi.getRGB(c, r);
         red = ((pix >> 16) & 0xff) / size;
         green = ((pix >> 8) & 0xff) / size;
         blue = (pix & 0xff) / size;
         histogram[red][green][blue]++;
    }
}
```

Figure 2. Original Java implementation of the image probability density function computation.

2.2 Hardware platforms used in this study

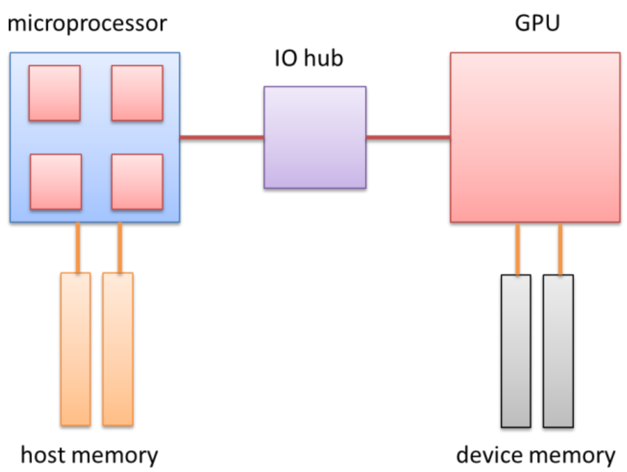
Two computer systems have been used in this study: 1) Intel based with Fermi GTX 480 GPU and 2) AMD based with ATI Radeon 5870 GPU. Table 1 contains technical characteristics of both systems. If not explicitly said, results reported in this report, such as the application profile shown above, were obtained on the Intel-based system which was found to be better performing.

	Intel-based system	AMD-based system
Processor	3.3 GHz single 4-core Core i7	2.8 GHz dual 6-core Istanbul
Memory	24 GB DDR3	32 GB DDR2
GPU	NVIDIA GeForce GTX 480	ATI Radeon HD5870
PCIe interface	2.0	2.0

Table 1. Characteristics of the two computer systems used in this study.

2.3 GPU kernel offload programming model

Figure 3, left, shows a typical architecture of a GPU-enabled computing system. A GPU is added to the conventional multi-core system via the Peripheral interface (PCIe). GPU card contains its own memory (referred to as the *device memory*)



- **Step 1: discover and connect to the device(s)**
- **Step 2: allocate memory on the device and copy input data from host memory to the device memory**
- **Step 3: launch the compute kernel and wait until it is done**
- **Step 4: copy results back from the device to host memory**
- **Step 5: detach from the device**

Figure 3. left: Architecture of a typical GPU-based computing system. Right: Typical sequence of steps nessesary to implement kernel offload to the GPU.

Executing a computational kernel on the GPU involves several steps, as shown in Figure 3, right. First, a GPU device is discovered and configured. This step is implicitly performed by the NVIDIA CUDA SDK when a call to CUDA SDK is made. However, when using OpenCL, it is programmer's responsibility to perform this step explicitly. Second, data from the host (image data in our case) is transferred to the memory accessible by the GPU (device memory). This transfer occurs over the PCIe interface and adds to the overall execution time. Next, the actual GPU kernel is invoked. When the kernel execution finishes, computed results are transferred from the device memory to the host memory. The programming model that implements these steps is referred to as *kernel offload model* because the execution of (presumably) computationally intensive portion of the code is offloaded to the GPU for accelerated execution.

2.4 Performance measurements

When comparing performance of the code executed on the GPU with the original Java code executed on the host by the Java virtual machine, it is important to measure and report the execution time that includes all the overheads associated with the use of a particular computing hardware. In this study we report execution time measured within the Java code. In case of the pure Java implementation, the time measured reflects the time spent executing the computation by the Java virtual machine (Figure 4, top). In case of the C port of the computational kernel, the time measured includes the overhead associated with calling a C function from Java, execution of the C function, and the overhead of copying results computed by the C function to the Java data structures (Figure 4, middle). In case of the GPU implementation, the measured time reflects all the overheads associated with the invocation of a C function from Java virtual machine, overheads due to the data transfer from the host memory to the device memory, GPU kernel execution time, and the device to host data transfer time (Figure 4, bottom).

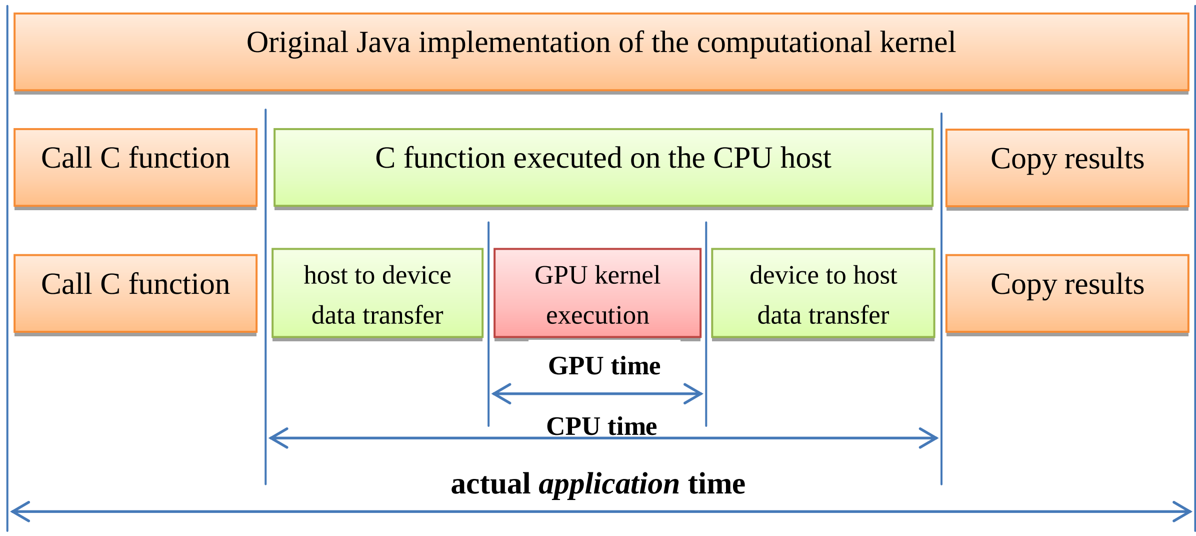


Figure 4. Measured application time includes all the overheads involved in using the underlying hardware.

3 Technical activities, findings, and results

3.1 Java code optimization

Further profiling of the doc2learn code shown in Figure 2 revealed that `bi.getRGB(c, r)` function is responsible for the vast majority of the time spent in this code. `getRGB` function performs color space conversion, if needed. But in the majority of cases images are stored in the RGB format and such color space conversion is unnecessary. Therefore, for images that are already in RGB color space we can eliminate this call as shown in Figure 5. This simple optimization improves the execution of the image probability density function estimation by a factor of ~6, reducing the image processing part for has.pdf example from 1,655 ms to 274 ms. In the rest of this study we use this updated code for performance comparison analysis. Figure 6 contains updated application execution profile shown in Figure 1 after this code optimization is applied.

```
// compute histogram for image
int red, green, blue;
byte[] data = ((DataBufferByte)bi.getRaster().getDataBuffer()).getData();
for (int i =0; i < data.length; i+=3){
    red =(data[i] & 0xff) / size;
    green = (data[i+1] & 0xff)/ size;
    blue = (data[i+2] & 0xff) / size;
    histogram[red][green][blue]++;
}
```

Figure 5. Improved Java implementation of the image probability density function computation.

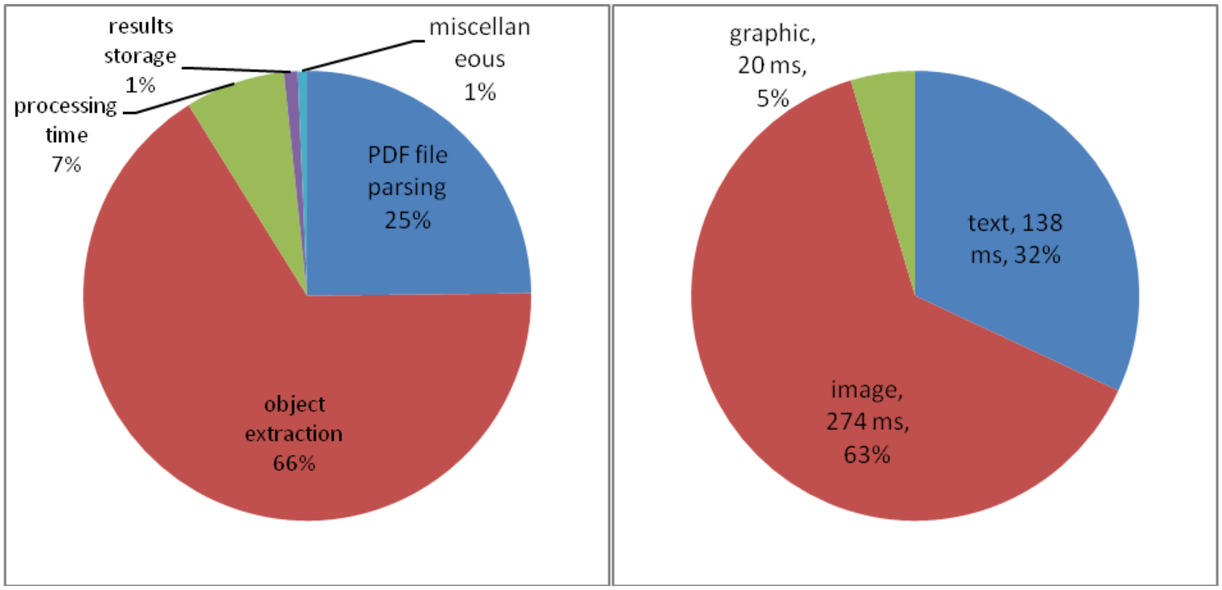


Figure 6. Doc2learn execution profile when using the improved Java image analysis code.

3.2 Java to C port

Java-C interface is implemented using Java Native Interface (JNI). On the Java side of the application, we only need to obtain a pointer to the image data and pass it to the C subroutine which is compiled using a C compiler, such as ICC or GCC. Figure 7 shows how the C subroutine is called in place of the code shown in Figure 5, Figure 8 shows C implementation that corresponds to Java implementation shown in Figure 4.

```
int bincolor = (int) Math.pow(BINS, 1.0 / 3.0);
int size = 256 / bincolor;
int[][][] histogram = new int[bincolor][bincolor][bincolor];
int pix, red, green, blue;

byte[] data = ((DataBufferByte)bi.getRaster().getDataBuffer()).getData();
ImageHistCPU ihg = new ImageHistCPU();
int[] hist_from_cpu = ihg.computeImageHist(data);  // compute histogram in C function

for(red = 0; red < bincolor ; red++) {  // copy results back to Java storage
 for(green = 0; green < bincolor ; green++) {
  for(blue = 0; blue < bincolor ; blue++) {
    histogram[red][green][blue]=hist_from_cpu[red*bincolor*bincolor+green*bincolor+blue];
  }
 }
}
```

Figure 7. Source code showing how histogram computation is replaced with a call to a C function.

Execution time of the Java version of this code using has.pdf data file is 274 ms. Execution time of the corresponding C implementation compiled with GCC compiler using highest level of optimization (-O3) is 109 ms *as measured on the Java side of the application*, or 2.5 times faster than the native Java implementation. Updated application profile is shown in Figure 9.

Note that neither GCC nor ICC compilers are able to vectorize the code due to the data dependency on `histogram[]`. The code, however, can be restructured to process several image pixels in stripes of 8 or 16 and maintain the corresponding number of independent histogram arrays that are summed up at the end. The compilers however are still not able to vectorize this restructured code because of the type of data primitives (unsigned char) used. If we promote data type to `float`, compilers report that the code can be vectorized, but such vectorization will not be effective. Further analysis is needed why this is the case.

```
int bins_per_color = (int)pow(BINS, 1.0/3.0);
int size = 256 / bins_per_color;

for (int i=0;i < length; i+=3) {
  int red = data[i] / size;
  int green = data[i+1] / size;
  int blue = data[i+2] / size;
  int index = red*bins_per_color*bins_per_color + green*bins_per_color + blue;
  histogram[index]++;
}
```

Figure 8. C implementation of the image histogram computation.

We also attempted to restructure the data by splitting three color channels in separate arrays and then applying the same vectorization strategy: process 8 or 16 pixels in stripes. With suitable data type conversions, ICC compiler was able to vectorize the code, but its performance was slightly worse than the performance of the original code shown in Figure 8. Since now three separate arrays are used, data caching becomes less efficient, resulting in increased cache misses, which leads to lower performance.

Some experimentation still remains to be done with manual vectorization using either intirincics supported by the compilers, or writing the code in assembly language. Also, another direction is to explore the use of multiple CPU cores available in modern microprocessors.

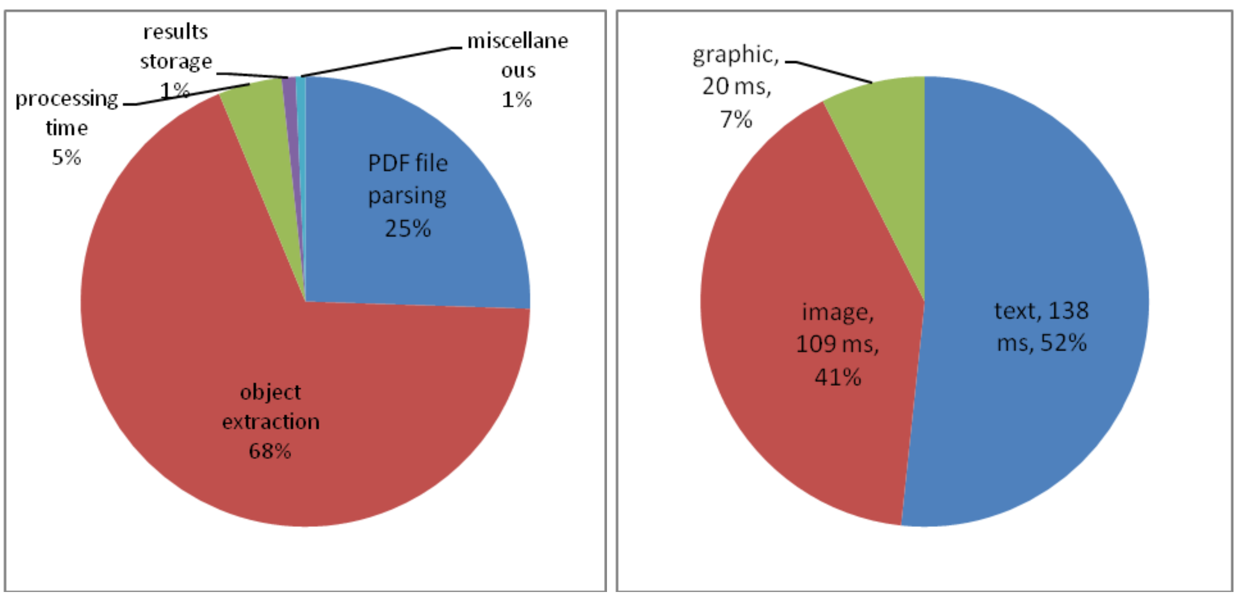


Figure 9. Doc2learn execution profile when using the C-based image analysis code.

3.3 CUDA C implementation

CUDA C NVIDIA GPU implementation follows the traditional kernel offload programming model described earlier. A C function is invoked from the Java application. The C function copies image data from the host memory to the device memory, calls the kernel GPU function and waits until it completes, copies results from the device memory to the host memory, and returns the execution control to the Java application. The GPU kernel function was initially implemented with each thread block computing its own copy of the histogram stored in the shared memory. Multiple copies of the histograms are then merged at the end. Source code of this implementation is shown in Figure 10. Table 2 shows the execution time of this kernel on the Intel/NVIDIA based system as well as several other kernels when invoked with a 3133x3233 pixels image test.

We implemented several modifications to this kernel aimed at eliminating conflicts when updating histogram bins and reducing number of memory bank conflicts when accessing histogram data in the shared memory. Table 2 provides brief descriptions of the main optimization techniques applied in each kernel generation and Figure 11 contains the source code of the best-performing GPU kernel.

Kernel version	CPU time (ms)	Data movement time (ms)	GPU kernel time (ms)
Non-vectorized CPU implementation (Figure 8)	19		
GPU kernel 1 (Figure 10): each thread block operates on its own copy of the histogram		5.42	10.94
GPU kernel 2: each thread operates on its own copy of the histogram		5.42	8.28
GPU kernel 3: 16-bit histogram is used instead of 32-bit, grid block size is adjusted to avoid overflow		5.42	4.67
GPU kernel 4: histogram is transposed to reduce the shared memory bank conflicts		5.42	1.16
GPU kernel 5: manipulate thread index to reduce shared memory bank conflicts in the assignment phase		5.42	1.16
GPU kernel 6 (Figure 11): manipulate thread index to reduce shared memory bank conflicts in the histogram merge phase		5.42	1.11

Table 2. CPU and GPU kernel execution time for a 3133x3233 pixels test image.

Note that while the GPU kernel execution time decreases with each optimization technique applied, the data transfer time remains constant. The best performing GPU kernel (#6) executes the computation of the histogram on the 3133x3233 pixels test image in just 1.11 ms, or 6.53 ms when taking into account CPU-GPU data transfer overhead. This compares to 19 ms (2.9x speedup) when compared to the C implementation or to 39 ms when taking into account the additional 20 ms overhead due to the C function invocation from doc2learn Java program and corresponding data fetch in the C program necessary to access image data (JNI overhead). Thus, taking into account all overheads, the overall speedup of the GPU implementation compared to the C-based CPU implementation as seen by the end user is only ~1.5x.

```
__global__ void histogramKernel1(void* imagedata, unsigned int n, unsigned int* result)
{
  __shared__ unsigned int hist[64];
  int i, idx = blockIdx.x*blockDim.x + threadIdx.x;
  if (threadIdx.x < 64)
    hist[threadIdx.x] = 0;

  __syncthreads();

  int total_num_threads= blockDim.x * gridDim.x;
  int num_pixels = n /3 ;
  unsigned char* bytedata = (unsigned char*)imagedata;

  for (i =idx; i< num_pixels;i += total_num_threads) {
    unsigned char r = bytedata[3*i];
    unsigned char g = bytedata[3*i + 1];
    unsigned char b = bytedata[3*i + 2];
    r = r >> 6;
    g = g >> 6;
    b = b >> 6;
    int bin_idx = (r << 4) + (g << 2) +  b;
    atomicAdd( &hist[bin_idx], 1);
  }

  __syncthreads();

  if(threadIdx.x < 64)
    result[blockIdx.x * REAL_BINS + threadIdx.x] = hist[threadIdx.x];

  return;
}
```
Figure 10. Initial GPU Kernel implementation (kernel 1 in Table 2).

We also tried to overlap image data transfer with the GPU computation, but in order to do so the image data on the host needs to be located in pinned memory (memory that is never swapped to the secondary storage) as opposite to paged memory, which resulted in a large penalty due to the need for an extra copy of image data on the host.

Figure 12 contains updated application execution profile previously shown in Figure 9 using NVIDIA GPU hardware to speed up the execution of image analysis part of doc2leanr software and has.pdf example.

```
__global__ void histogramKernel6(void* imagedata, unsigned int n, unsigned int* result)
{
  __shared__ unsigned short hist[64*64];
  int i, tid = threadIdx.x ;
  tid = ((tid & 0x01)<<4) | ((tid & 0x10) >> 4) | (tid & 0xee);
  int idx = blockIdx.x*blockDim.x + tid;
  if (tid < 64)
    for(i=0;i < 64;i++)
      hist[i*64+tid] = 0;

  __syncthreads();

  int total_num_threads= blockDim.x * gridDim.x;
  int num_pixels = n /3 ;
  unsigned char* bytedata = (unsigned char*)imagedata;

  for(i =idx; i< num_pixels;i += total_num_threads) {
    unsigned char r = bytedata[3*i];
    unsigned char g = bytedata[3*i + 1];
    unsigned char b = bytedata[3*i + 2];
    r = r >> 6;
    g = g >> 6;
    b = b >> 6;
    int bin_idx = (r << 4) + (g << 2) +  b;
    hist[bin_idx*64 + tid] += 1;
  }

  __syncthreads();

  unsigned short temp = 0;
  for (i=0;i < 64;i++)
    temp += hist[threadIdx.x*64 + ((i+threadIdx.x*2)&0x3f)];

  result[blockIdx.x * REAL_BINS + threadIdx.x] = temp;

  return;
}
```

Figure 11. Optimized GPU kernel implementation (kernel 6 in Table 2).

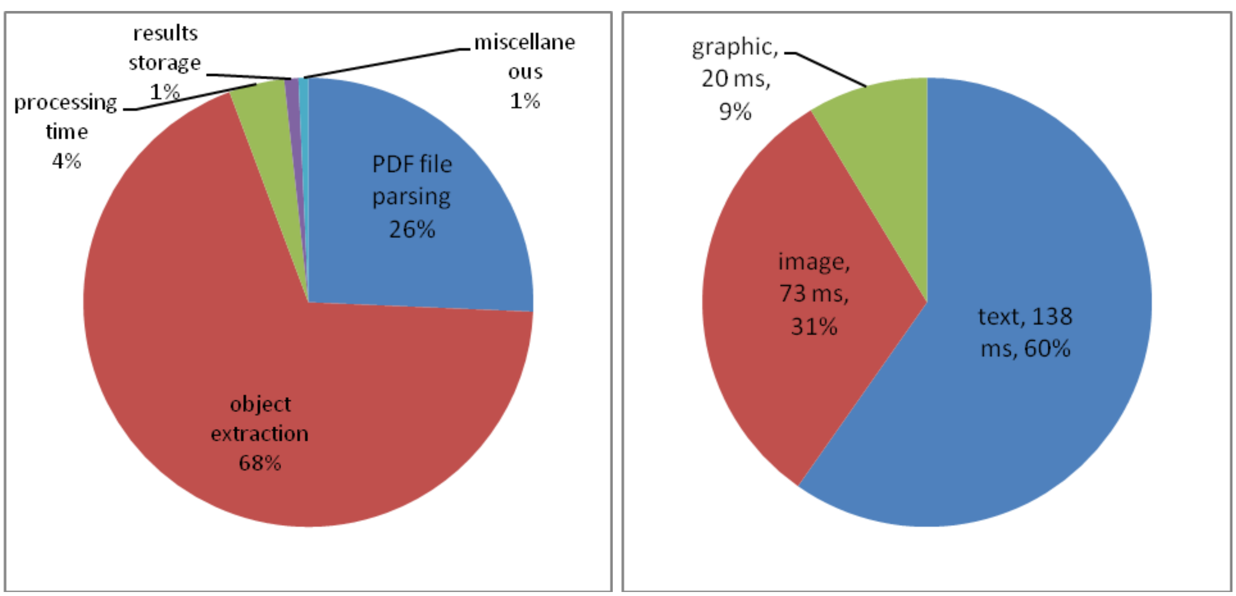


Figure 12. Doc2learn execution profile when using the NVIDIA CUDA GPU image analysis code.

3.4 OpenCL implementation

We implemented similar variations of the GPU kernels in OpenCL targeting both NVIDIA and AMD GPUs. OpenCL implementations of the kernels follow very closely our CUDA kernel implementations when the necessary hardware features are supported by OpenCL, which is not always the case.

For the 3133x3233 pixels test image, best OpenCL result obtained on the NVIDIA GPU is with kernel 6: 1.28 ms for the actual kernel execution and 5.48 ms for the data transfer. This is only slightly worse that the native CUDA implementation.

For the 3133x3233 pixels test image, best OpenCL result obtained on the AMD GPU is with the kernel 1: 2.79 ms for the kernel execution and 38.12 ms for the data transfer. Unfortunately data transfer on the AMD GPU platform is prohibitively long. The PCIe interface supports data transfer rates similar to those observed on the NVIDIA hardware and there is no technical reason for such a poor performance; we believe AMD GPU drivers are not tuned for the best performance.

3.5 Performance study to understand the impact of image size

We investigate performance of different implementations of the image analysis algorithm as the function of image size. We consider image sizes ranging from 128x128 pixels to 8192x8192 pixels and seven implementation/platform configurations:

- Java implementation with the optimized Java code running on a single core of 2.8 GHz AMD Istanbul processor
- Java implementation with the optimized Java code running on a single core of 3.3 GHz Intel Core i7 processor
- C implementation running on a single core of 2.8 GHz AMD Istanbul processor
- C implementation running on a single core of 3.3 GHz Intel Core i7 processor
- CUDA C implementation running on NVIDIA GTX 480 GPU installed on the 3.3 GHz Intel Core i7 platform
- OpenCL implementation running on NVIDIA GTX 480 GPU installed on the 3.3 GHz Intel Core i7 platform
- OpenCL implementation running on ATI Radeon HD5870 GPU installed on the 2.8 GHz AMD Istanbul platform

Table 3 contain raw measurements obtained in this study. These measurements are used to generate the plots shown in Figures 13-15.

Figure 13 provides a plot of the execution time for seven implementation/platform configurations as a function of image size. In the measurements provided in this plot we included all relevant overheads, such as JNI overhead and PCIe data transfer overhead. In other words, the measured execution time is what the user sees in the Java application that invokes one or another type of kernel (Java, C, or GPU). From this plot, we can make several important observations:

- Both Java and C implementations perform substantially worse on the 2.8 GHz AMD Istanbul platform compared to the 3.3 GHz Intel Core i7 platform. It is most likely due to the Java and GCC compiler ports that do not fully take into account all AMD processor’s architecture features.

- On the 3.3 GHz Intel Core i7 platform, the code in which Java-based computation is replaced with a call to a C-based computation executes faster with a near-constant speedup for all image sizes tested in this study.
- For a sufficiently large image size, all GPU-based implementations outperform the CPU-based implementations.
- CUDA implementation executed on NVIDIA GTX 480 GPU platform outperforms OpenCL implementations running on both platforms.

Image Size	**AMD CPU host run time (ms)**				**Intel CPU host run time (ms)**			
	java-based	C-based			java-based	C-based		
		C loop	JNI overhead	total		C loop	JNI overhead	total
128x128	0.79	0.68	*0.05*	0.73	0.26	0.03	*0.04*	0.07
256x256	2.93	2.57	*0.16*	2.73	0.68	0.10	*0.07*	0.17
512x512	11.13	10.50	*0.44*	10.94	2.63	0.42	*0.20*	0.62
1024x1024	49.22	42.79	*4.20*	46.99	10.58	1.71	*1.91*	3.62
2048x2048	185.42	172.91	*18.11*	191.02	42.23	7.49	*11.08*	18.57
4096x4096	741.33	692.66	*65.91*	758.57	168.66	27.54	*30.58*	58.12
8192x8192	2969.32	2760.50	*264.07*	3024.56	672.13	110.59	*121.85*	232.44

Image Size	**NVIDIA GTX 480 GPU run time (ms)**							
	CUDA-based				OpenCL-based			
	GPU kernel	PCIe overhead	JNI overhead	total	GPU kernel	PCIe overhead	JNI overhead	total
128x128	0.05	0.04	*0.12*	0.21	0.12	0.23	*2.45*	2.80
256x256	0.06	0.08	*0.17*	0.31	0.13	0.29	*2.65*	3.06
512x512	0.08	0.26	*0.29*	0.63	0.14	0.48	*2.82*	3.44
1024x1024	0.17	0.73	*2.01*	2.91	0.24	0.96	*4.36*	5.56
2048x2048	0.53	2.32	*7.71*	10.56	0.64	2.59	*10.17*	13.40
4096x4096	1.96	8.76	*30.90*	41.62	2.13	8.99	*32.91*	44.03
8192x8192	7.77	34.49	*123.24*	165.50	8.20	37.60	*124.53*	170.33

Image Size	**ATI Radeon 5870 GPU run time (ms)**			
	OpenCL-based			
	GPU kernel	PCIe overhead	JNI overhead	total
128x128	0.36	0.44	*0.62*	1.42
256x256	0.36	0.61	*0.92*	1.89
512x512	0.41	1.34	*1.11*	2.86
1024x1024	0.35	15.24	*4.90*	20.49
2048x2048	0.76	20.39	*17.30*	38.45
4096x4096	2.53	39.38	*67.00*	108.91
8192x8192	6.83	108.41	*263.60*	378.84

Table 3. Performance measurements for different implementations and architectures.

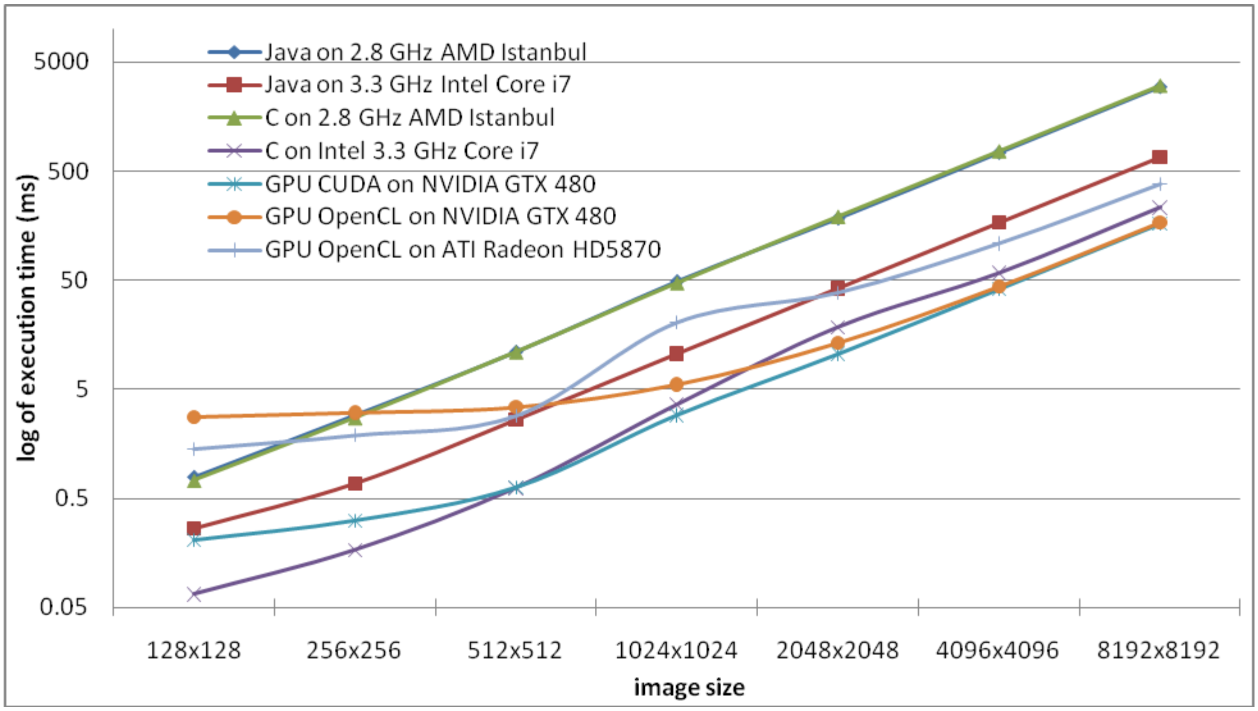


Figure 13. Logarithmic plot of the execution time as a function of image size.

Figure 14 provides additional insights into performance of the C and GPU implementations. In this figure, we plot the following ratios that indicate relative speedups:

- Java time to C time, including JNI overhead, on the Intel 3.3 GHz Core i7 platform. This is what the user sees in the Java application that invokes a C function that processes the image.
- Java time to C time, NOT including JNI overhead, on the Intel 3.3 GHz Core i7 platform. This is what the user would see when comparing the Java-based application with an application which is entirely C-based. This measure shows the full C over Java advantage.
- Intel 3.3 GHz Core i7 time spent by the C-based kernel to the time spent transferring data between the host and NVIDIA GTX 480 GPU and executing the kernel on the NVIDIA GTX 480 GPU. This is GPU vs CPU speedup, including data transfer over PCIe bus overhead.
- Intel 3.3 GHz Core i7 time spent by the Java-based implementation to the time spent by the Java-based code that calls a C-based implementation that calls the GPU-based implementation. All the overheads, JNI and PCIe bus data transfer, are included in the GPU-based implementation. This is what the user sees in the Java application that invokes a GPU-based function that processes the image.
- Intel 3.3 GHz Core i7 time spent by the Java-based implementation to the time spent by the C-based implementation that calls the GPU-based implementation, excluding JNI overhead. This is GPU vs Java speedup, including data transfer over PCIe bus overhead.

From this plot, we can make the following observations:

- Replacing optimized Java code with the call to a C-based function results in on average 3x speedup. This speedup takes into account the overhead of calling a C function from the Java application.
- We observe an average 6x speedup when comparing Java computation time with the corresponding C-based code computation time, assuming that there is a full C-based application. The speedup is even greater, up to 8.8x, for smaller images. This observation indicates that if the image analysis algorithm used in doc2learn was implemented as a stand-alone C program, it would have executed 6 times faster than the current doc2learn all-Java implementation.
- For small images, GPU implementation is actually slower than the C-based CPU implementation. For image sizes close to 512x512, the CPU and GPU implementations break even. Maximum GPU speedup for sufficiently large images is only 2.6x as compared to the C-based CPU implementation.
- Replacing optimized Java code with the call to a C function that calls a GPU function results in the speedup ranging from 1.2x for small images to 4x for large images. This is what the user sees from the standpoint of the Java application.
- Finally, if we compare full Java-based implementation with the C-based implementation that calls a GPU kernel, we observe a speedup of almost 3x for small images to almost 16x for large images. This observation indicates that if the image analysis algorithm used in doc2learn was implemented as a stand-alone C program that uses NVIDIA GTX 480 GPU, it would have executed up to 16 times faster than the current doc2learn all-Java implementation.

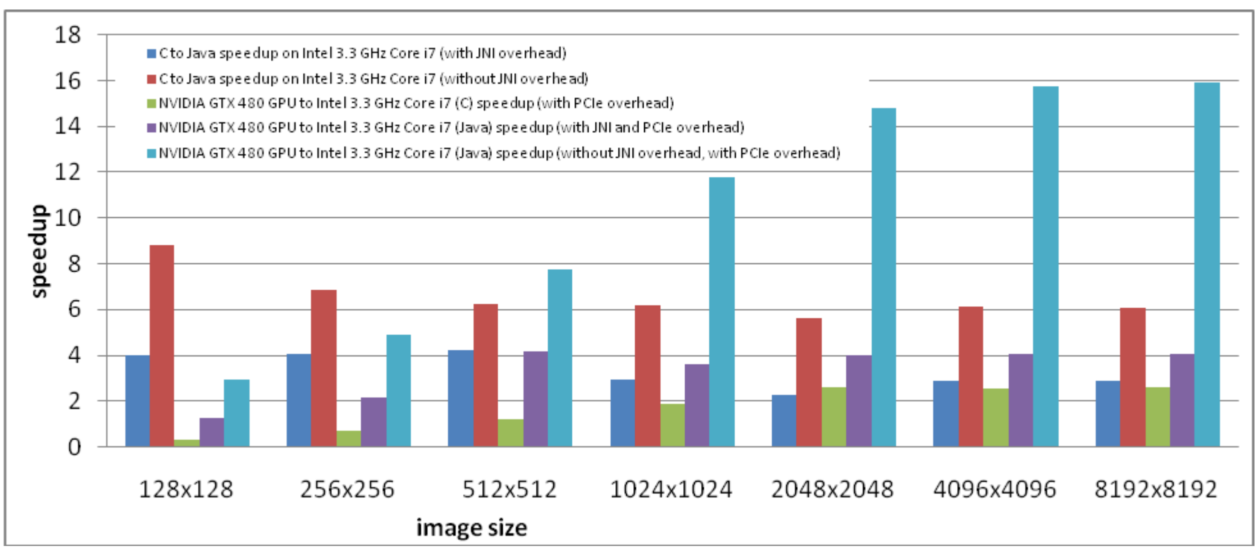


Figure 14. Speedup as a function of image size.

Figure 15 provides some additional insights into the image analysis code execution profile for two image sizes and three platforms. For a sufficiently large image, GPU-based implementation suffers from a substantial JNI Java-to-C interface overhead.

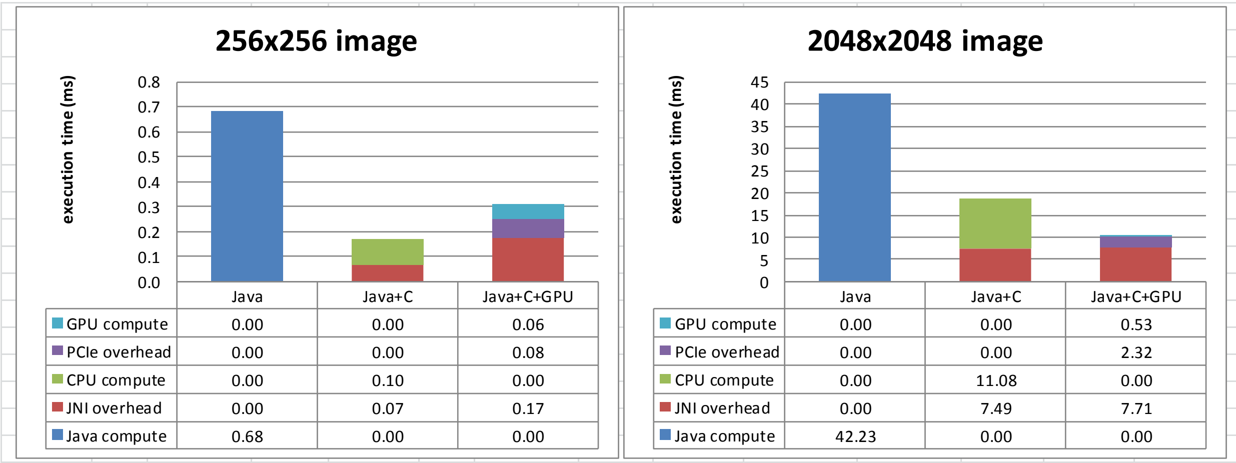


Figure 15. Execution profile comparison for two image sizes.

3.6 Performance study to understand the impact of the number of images

We investigate performance of different implementations of the image analysis algorithm as the function of the number of images embedded in the PDF file. We consider three implementations using Intel platform:

- Java implementation with the optimized Java code running on a single core of 3.3 GHz Intel Core i7 processor
- C implementation running on a single core of 3.3 GHz Intel Core i7 processor
- CUDA C implementation running on NVIDIA GTX 480 GPU installed on the 3.3 GHz Intel Core i7 platform

The dataset used in this study consists of 100 PDF files that contain only images. Each PDF file contains some number of randomly generated images of a fixed size. Image sizes include 50x50, 100x100, 150x150, and 200x200 pixels and image count per PDF file is from 10 to 250. This synthetic dataset was generated by Peter Bajcsy's team and it is deemed to be statistically representative of a set of PDF files that the team has been working with.

Table 4 lists all the image sizes and the number of images per PDF file. It also lists the overall image processing time for each of the PDF files using each of the three algorithm implementations. Figure 16 provides a graphical representation of the data from Table 4. The measured execution time confirms our prior findings:

- For small images, C-based implementation outperforms both the Java-based and GPU-based implementations

	JAVA				C				GPU			
	Image size				Image size				Image size			
count	50x50	100x100	150x150	200x200	50x50	100x100	150x150	200x200	50x50	100x100	150x150	200x200
10	11	10	13	15	8	9	9	9	12	13	11	11
20	19	20	23	27	18	17	18	20	22	24	22	23
30	28	34	34	40	26	30	27	30	32	32	33	34
40	37	43	45	53	37	37	38	41	43	43	45	46
50	46	50	57	67	44	45	46	51	54	54	56	59
60	56	62	69	79	54	54	56	58	64	66	68	70
70	65	71	80	92	63	65	67	72	75	74	81	82
80	78	82	94	110	72	73	78	80	83	86	87	91
90	87	92	107	124	82	83	87	88	97	99	102	107
100	131	342	135	175	105	283	125	106	120	478	146	120
110	110	125	132	151	104	105	111	114	123	125	129	131
120	118	128	148	168	119	113	120	136	137	136	145	145
130	129	140	156	178	125	127	131	132	146	145	153	156
140	139	149	169	193	130	134	136	141	153	159	159	174
150	146	162	179	205	142	146	151	156	167	172	175	183
160	156	172	189	224	146	154	154	162	180	182	185	194
170	164	184	198	232	159	168	166	173	186	189	193	197
180	180	195	213	253	168	168	170	187	203	202	209	212
190	186	201	224	260	178	182	190	195	218	215	224	219
200	199	212	239	282	188	193	204	201	226	219	229	237
210	199	227	259	289	197	202	201	209	231	238	246	244
220	209	230	260	299	205	205	221	228	237	239	255	260
230	220	237	268	310	216	225	230	239	257	261	265	272
240	228	250	292	327	217	231	233	250	255	265	267	275
250	237	263	290	344	230	231	241	250	271	275	277	287

Table 4. Image processing time (in ms) for different implementations using synthetic dataset consisting of 100 PDF files with varying number of images (from 10 to 250) per file and different image size (from 50x50 to 200x200 pixels).

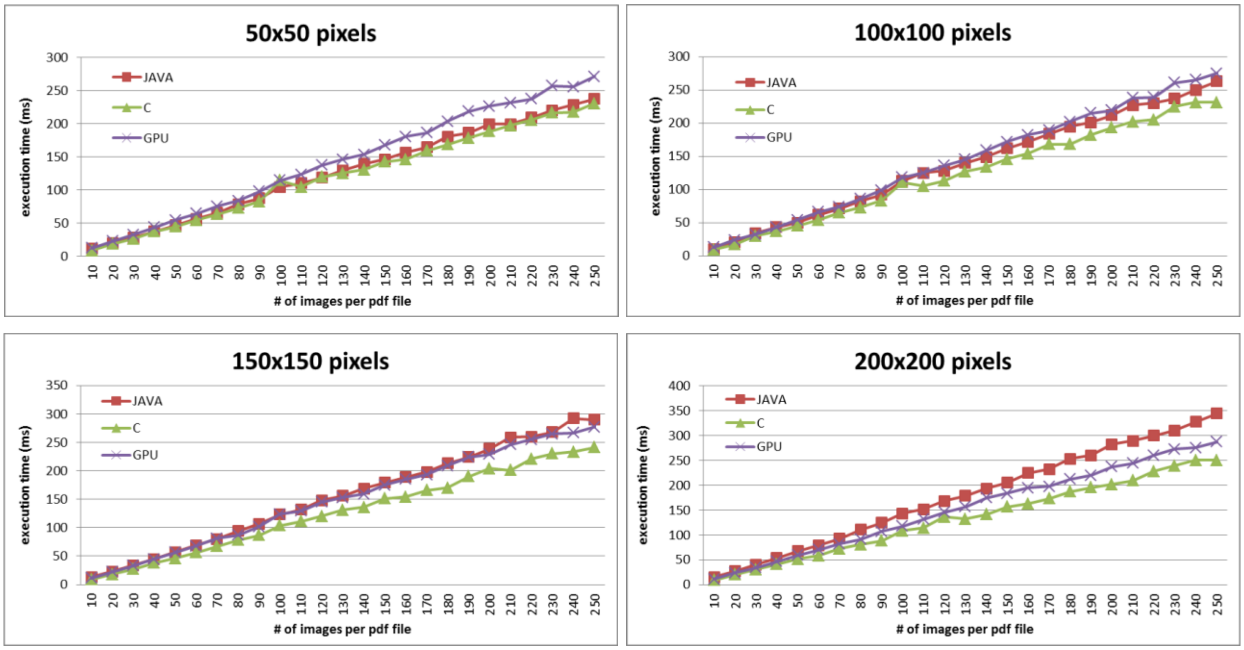


Figure 16. Execution time as the function of the number of images per PDF file.

4 Conclusions and future work

4.1 Implications for doc2learn image analysis algorithm

The image probability density function computation algorithm implemented in Java in doc2learn software can be accelerated by a factor of 6x if the entire doc2learn image analysis software is re-implemented in C, or by a factor of almost 16x if it also uses an NVIDIA GTX 480 GPU. Actual GPU speedup largely depends on the image size: for images less than 512x512 our CPU implementation outperforms the GPU implementation.

Calling a GPU-based implementation from the existing doc2learn Java-based code is still beneficial as it provides up to 4x speedup for sufficiently large images. But another factor of 4x speedup can be achieved by porting the entire image analysis software suite to C and using GPU kernels within the C-based code.

4.2 Implications for doc2learn application

Doc2learn execution profile shown in Figure 6 indicates that only about 4% of the overall execution time for the given PDF file example is spent on the image processing part. Speeding it up by any factor will not make much of a difference for the entire application. Said that, GPU acceleration may be still beneficial for PDF files containing very large images or embedded videos.

Doc2learn also implements probability density function computation algorithms for text and vector graphics. These data types exhibit less regular memory access patterns and require much large histograms to be stored. Because of this, they are less suitable for GPU implementation as compared to image histograms.

4.3 CUDA vs OpenCL

At this point, CUDA-based implementation outperforms the OpenCL based implementation, but it does not provide portability across GPU platforms. We have not investigated OpenCL implementation for a multi-core architecture, but from our prior experience we know that platform-specific tuning will be required to achieve good performance with OpenCL on any architecture. The OpenCL code written for one architecture will execute on another architecture, but not at its full potential.

4.4 Future work

In the second quarter of this project, we will develop a stand-alone C implementation of the image extraction component of doc2learn and will integrate the developed image probability density function computation algorithm (both the CPU and GPU implementations) with the stand-alone image extractor. We will base our work on xpdf C++ library which has all the components necessary to quickly assemble the PDF image extraction framework. We will investigate how to extend the CPU implementation of the histogram computation to the multi-core architecture of modern CPUs. We will conduct a study how the proposed stand-alone implementation compares to the original doc2learn implementation, with regards to both the image processing time and the object extraction time, which is significant in current doc2learn implementation. We will use the developed stand-alone framework to analyze power consumption of the CPU and GPU implementations on a set of benchmark PDF files.

We will investigate other image comparison algorithms and their suitability for GPU acceleration. *Versus* project currently under development by Peter Bajcsy's team provides a framework for using third-party image characterization algorithms. We will investigate pros and cons of extending this framework to include GPU-based image comparison algorithms.