# Evaluation of 'OpenCL for FPGA' for Acceleration and DAQ in HEP

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Prepared By: Srikanth Sridharan, Paolo Durante, Niko Neufeld, Daniel Campora

#### Abstract

The increase in the data acquisition and processing needs of High Energy Physics experiments has made it even more essential to use FPGAs to meet those needs. However harnessing the capabilities of the FPGAs has been hard for anyone but expert FPGA developers. The arrival of OpenCL, and the two major FPGA vendors supporting it, offers an easy software-based approach to taking advantage of FPGAs in applications such as High Energy Physics. OpenCL is a language for using heterogeneous architectures in order to accelerate applications. With OpenCL it has become easier to port code between GPUs, FPGAs & other accelerators and using FPGAs has become as easy as using GPUs. A comparison of their performance is made. OpenCL has the potential for a massive gain in productivity and ease of use enabling non FPGA experts to design, debug and maintain the code. Also, FPGA power consumption is much lower than other implementations. However, FPGAs are capable of far more than acceleration, hence it is interesting to explore if OpenCL can be used to take advantage of FPGAs for more generic applications. To answer this question, especially in the context of High Energy Physics, a DAQ module was also tested for implementation with OpenCL on FPGAs<sup>1</sup>. The challenges on using OpenCL for a DAQ application and their solutions, together with the performance of the OpenCL based acceleration are discussed. Many of the design elements needed to realize a DAQ system in OpenCL already exists, mostly as FPGA vendor extensions, but a small number of elements were found to be missing. This paper describes one of the first attempts to explore the use of OpenCL for applications outside the acceleration workloads.

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### 1. Introduction

The proposed upgrade for the Large Hadron Collider LHCb experiment at CERN envisages a system of 500 data sources, each generating data at 100 Gbps. The acquisition and processing of this is a challenge even for state-of-the-art FPGAs. This challenge has two parts, one is Data Acquisition (DAQ) and the other Algorithm Acceleration, the latter not necessarily immediately following the former.

For the algorithm acceleration part, the Hough transform [1] was implemented in OpenCL. This is a method to identify patterns from points in 2D/3D space and can be used to identify particle tracks from hits in the VELO detector elements. Variations of this algorithm are also used for feature identification on the data from other detectors. This work explored the ease of use of implementing algorithm acceleration on OpenCL for FPGA. To enable comparison, the same algorithm was ported to Altera FPGA, Nvidia GPU as well as an Intel Xeon Phi. The results of the comparison are analyzed and a performance improvement for the FPGA has been presented.

For the Data Acquisition, a Header Generator module was needed to packetize the streaming data coming in from the front-end electronics of the detectors, for easy access and processing by the servers. This necessitates FPGA architectures that not only handle the data generated by the experiment in real-time, but also dynamically adapt to potential inadequacies of other components, such as the network and PCs, while ensuring system stability and overall data integrity. Since the data source has no flow control, this module needs to modify the stream data by dropping datasets in a controlled fashion if a back pressure signal is generated by the downstream modules. A front-end source emulator capable of generating the various data patterns that can act as a test bed to validate the functionality and performance of the Header Generator was also needed. Such a system was earlier designed and realized in VHDL. [2]

While this process has been traditionally carried out using hardware description languages (HDLs), the possibility exists of using OpenCL to design a DAQ system. OpenCL has the potential to simplify the development cycle of the applications, and make it easier for physicists, who are more familiar with traditional software, to understand the system and make modifications in the future. This is challenging due to the fact that the OpenCL language is designed for Parallel Processing and not really targeted at real-time DAQ and there are major challenges in representing the cycle-accurate data acquisition and processing system in OpenCL. However, OpenCL for FPGAs may be applicable from a high level synthesis perspective. Achieving this will enable the transition of the entire FPGA design flow for High Energy Physics applications to OpenCL, rather than just the algorithm acceleration portion that involves parallel processing.

## 2. FPGAs in High Energy Physics

FPGAs are used in HEP experimental setups for a variety of purposes. They are used initially for Data Acquisition to collate the streaming data coming off the front end electronics over multiple channels. Also there is a need for FPGAs in the low level trigger system where the acquired data need to be quickly processed to arrive at the trigger decisions. The custom nature of the solutions required and also the need to operate in high radiation environments make any other technology unsuitable for these purposes. ASICs are suitable only for high volume production and are unviable for these applications due to prohibitive costs.

#### 2.1. HDL based FPGA Design

The custom circuitries needed to implement these systems are traditionally designed using Hardware Description Languages like VHDL/Verilog. Programming in VHDL/Verilog is done at the Register Transfer Level (RTL) abstraction. These designs are then synthesized into netlists that are then placed and routed for the specific FPGA device and finally a bitfile, used to program the FPGA is generated. VHDL/Verilog being niche languages used by FPGA/ASIC designers, knowledge of them is not common among physicists or even software engineers. The RTL abstraction is a very low level representation and hence it is also difficult to design and debug extremely large designs. Moreover implementing the necessary logic/function in HDL is not enough - one needs to manually create memory hierarchies and also instantiate communication cores and link them to the design to keep the system supplied with data. All the control and glue logic needed to keep the design in synchronicity with other systems also need to be implemented. This just models the FPGA side of the system. In addition, the PC control software still needs to be implemented. However despite the shortcomings, it is nevertheless very flexible and versatile enough to implement anything from a custom processor, to a DAQ system or a co-processor/accelerator.

#### 2.2. OpenCL based acceleration on FPGA

The Khronos Group, the maintainer of the OpenCL specification [3], defines it as an open standard for parallel programming of heterogeneous systems. It is the first open, royalty-free standard for cross-platform, parallel programming of modern processors found in personal computers, servers and handheld/embedded devices. OpenCL has been in use for a while to take advantage of GPUs, DSPs and Manycore processors for parallelizable workloads. While FPGAs have always been capable of exploiting parallelism, their hardware based programming model makes taking advantage of them harder than using GPUs and other devices. That has now changed with the two major FPGA vendors supporting OpenCL-based acceleration by means of SDKs. These reduce OpenCL kernels to custom circuits that are subsequently synthesized to netlist and a bitstream is generated. The real advantage of OpenCL-based acceleration on FPGA is that the user only needs to focus on describing the logic for the computation itself. All the additional control logic, the PCIe core for communication and data transfer to and from the PC and the necessary memory hierarchy plus the memory controllers, are automatically generated by the tool. For instance, the tasks of transferring data to the FPGA, executing the kernel, and then retrieving the results is reduced to three simple API calls as follows:

Copy Data Host  $\rightarrow$  FPGA: clEnqueueWriteBuffer( ... );

Execute Kernel on FPGA: clEnqueueTask( ..., my\_kernel, ...);

clEnqueueNDRangeKernel( ..., my\_kernel, ...);

Copy Data FPGA  $\rightarrow$  Host: clEnqueueReadBuffer( ... );

This makes exploiting FPGAs for acceleration as easy as using GPUs. With the possibility of easily implementing or porting OpenCL applications to FPGA, exploiting FPGAs for acceleration has become as easy as using GPUs. While porting the code is only the first step, porting the performance is the real challenge. The following section looks at how the different architectures fare.

## 3. Algorithm Acceleration on FPGA with OpenCL: Hough Transformation

One of the claimed advantages of OpenCL is portability of code. Hence, for this evaluation, an existing implementation of the Hough Transform code for a GPU was used [4]. The Hough transform is a method to identify patterns from points in 2D/3D space. Variations of this algorithm are used to identify particle tracks from detector data of various experiments at CERN. The version used with the VELO (Vertex Locator) Detector for identifying straight line tracks was used for this evaluation. The existing kernels were used unmodified for the initial tests and minimal changes were done to the host code to allow for precompiled binaries as Altera's OpenCL compiler only supports offline compilation. Altera's OpenCL compiler version 14.1 was used. The code consisted of two kernels. The first was for a 2D Hough transform which is executed twice, for each of the XZ and YZ projections of the 3D particle hit data. The second was to find the overlap between the results of the two 2D transforms to compute 3D tracks. Along with the implementations for GPU and FPGA, one was also created for the Intel Xeon Phi MIC (Many Integrated Core) architecture and a Multi-core CPU.

#### 3.1. Comparison of unmodified kernels

The runtime figures of the two kernels over 3 runs are provided in Table 1. The same is represented in the Figures 1 and 2 in logarithmic and normal scale respectively. These runtimes were obtained by profiling for the start and finish of each kernel instance. These numbers are reported based on the internal clocks of the devices and hence the resolution of these values could be different. Also the total runtime of the program (host code plus kernels) is not shown due to the difference in the host system configurations. This also avoids the error due to the difference in online compilation (GPU, Xeon Phi and CPU) and offline compilation (FPGA). Intel OpenCL compiler was used for the CPU and Xeon Phi. Nvidia's and Altera's compilers were used for the GPU and FPGA respectively.

From figure 1 & 2, one can see that for kernel 1, the FPGA performs about 2.25 times faster than the GPU and about the same as Xeon Phi. Interestingly the CPU has the best runtime for kernel. This could be the result of the small dataset size and a high clock speed of the CPU. The runtime for kernel 2 on FPGA is abnormally high compared to other architectures, so the GPU and Xeon Phi are faster for kernel 2 by two orders of magnitude compared to the FPGA. The runtime for kernel 2 on FPGA goes out of bounds in normal scale and hence it is shown in red.

Algorithm Acceleration on FPGA with OpenCL: Hough Transformation



Figure 1. Run times of unmodified kernels in log scale



Figure 2. Run times of unmodified kernels in normal scale

#### 3.2. A little optimization

A quick look at the kernel code revealed that there are 3 for loops in the kernel and them being executed serially was reason for the long runtime. So the compiler was provided with a loop unroll hint as follows:

```
#pragma unroll
```

```
for (int i = 0; i < size; i++){
    Line1[i] = In1[gid1*size + i];
    Line2[i] = In2[gid2*size + i];
}
#pragma unroll
for (int i = 0; i < size; i++){
    #pragma unroll
    for (int j = 0; j < size; j++) {
        if (Line1[i] != 0 && Line1[i] == Line2[j]){
            count++;
        }
    }
}</pre>
```

Here the "#pragma unroll" directive instructs the Altera OpenCL compiler to unroll the for loops fully i.e. each of the iteration of the for loop is executed in parallel, since there is no interloop dependency. With this optimization directive the runtimes of kernel 2 were profiled again and the results of which are presented in Table 2 and Figure 3. Now the FPGA runs the kernel 2 twice as fast as Xeon Phi and 4 times as fast as the GPU.



Figure 3. Run times of loop unrolled kernel 2 with unmodified kernels

#### 3.3. Performance/Watt and some concluding words

While it might seem unfair to compare the numbers for FPGA with optimization directive with other architectures running vanilla kernels, it should be noted that the point of this paper is not to make a fool proof comparison of different architectures but to establish FPGA(with OpenCL) as an architecture that needs to be seriously considered. It should be possible to optimize the code for all the architectures to different extents and I'm sure we can obtain improved runtimes for GPU, Xeon Phi and the CPU too. In fact, it is possible that an optimized CPU version would beat the accelerators if overall run time of the entire algorithm for a single event is considered since it would save on costly data transfers between host and device memories. But for large number of events any of the accelerator should be better than the CPU is the kernels and their data transfers are pipelines, thereby hiding the data transfer latencies. (Such a comparison would require in depth understanding of all the architectures considered.) Similarly it would also be possible further improve performance for FPGA further as only one simple directive has been tried. For instance, there are also options to use OpenCL pipes or Altera Channels with FPGAs that would enable transfer of data between kernels without invoking costly memory access and transfers. This will reduce overall runtime on FPGAs further. There also exists further scope for extracting more parallelism from the Hough transform code, the lack of which could also be affecting the performance currently. This more or less establishes that FPGA perform as well as or better than other architectures. But even in the case where different architectures performs similarly or even when the raw performance of FPGA is lesser than other architectures, FPGAs still come out on top if one considers the power consumed, i.e. Performance/Watt. Figure 4 shows the Maximum power consumed by each of the device under comparison. While the actual power would be lesser depending on the workload, this is still indicative of how much more efficient the FPGA is compared to other architectures. Assuming identical raw performance, the FPGA has 8X higher Performance/Watt compared to the GPU and 11X compared to the Xeon Phi. The power figure of CPU is omitted in this comparison due to the fact that the different accelerators only run the kernels; the CPU on the other hand runs the kernels and host code on top of the Operating system and other overheads. A potential next step would be to measure the actual power consumption of the kernels on the different accelerators.



Figure 4. Maximum power consumed and their process technologies

#### 3.4. Additional remarks

Effort was also made to implement this algorithm on a Xilinx FPGA by compiling the OpenCL code with Xilinx's SDAccel 2015.1.4 tool, but unfortunately, the tool could not load the generated kernels onto hardware due to a bug. Hence tests could not be performed on the actual hardware.

FPGA (Altera Stratix V)       GPU (Nvidia GeForce GTX 680)         Kernel 1       Kernel 1       Kernel 1       Kernel 1         Kun 1       3570722       3512339       8052825491       7980800       7975776       17914624         Run 1       3570722       3512339       80528225491       7980300       7975776       17914624         Run 2       3556479       3570346       8052820352       7980352       7982176       17966112         Average       3560719.3       3530836       8052803192       7981856       7974848       17892672													
Kernel 1         Kernel 2         Kernel 1         Kernel 2           (XZ)         (YZ)         (Overlap)         (XZ)         (Overlap)           Run 1         3570722         3512339         8052825491         7980800         7975776         17914624           Run 2         3556479         3570336         8052820252         7980352         7980352         7980362           Run 3         3556479         3570346         8052803192         7980352         7980352         7980352           Average         3556479         3570346         8052903192         7981856         7974848         17892672		FPG/	A (Altera Sti	ratix V)	GPU (Nv	idia GeForce	; GTX 680)	MIC	(Intel Xeon I	ohi)	CPU (I	ntel Xeon E:	-2650)
(XZ)         (YZ)         (Overlap)         (XZ)         (Overlap)           Run 1         3570722         3512339         8052825491         7980800         7975776         17914624           Run 2         3554957         3509823         8052820525         7980352         7982176         179166112           Run 3         3556479         3570346         8052903192         7981856         7974848         17892672           Average         3560719.3         3530836         8052849645         7981802.7         7977600         17924469.3         2		Kernel 1	Kernel 1	Kernel 2	Kernel 1	Kernel 1	Kernel 2	Kernel 1	Kernel 1	Kernel 2	Kernel 1	Kernel 1	Kernel 2
Run 1         3570722         3512339         8052825491         7980800         7975776         17914624           Run 2         3554957         3509823         8052820252         7980352         7982176         17966112           Run 3         3556479         3570346         80522903192         7981856         7974848         17892672           Average         3560719.3         3530836         80522849645         7981802.7         7977600         17924469.3		(XZ)	(XZ)	(Overlap)	(XZ)	(XZ)	(Overlap)	(XZ)	(XZ)	(Overlap)	(XZ)	(XZ)	(Overlap)
Run 2         3554957         3509823         8052820252         7980352         7982176         17966112           Run 3         3556479         3570346         8052903192         7981856         7974848         17892672           Average         3560719.3         3530836         8052249645         7981002.7         7977600         17924469.3         3580836	Run 1	3570722	3512339	8052825491	7980800	7975776	17914624	3749897	3783748	8824323	767517	951824	21787752
Run 3         3556479         3570346         8052903192         7981856         7974848         17892672           Average         3560719.3         3530836         8052849645         7981002.7         7977600         17924469.3         3580836	Run 2	3554957	3509823	8052820252	7980352	7982176	17966112	3445624	3152602	8426870	1972570	751718	24285992
Average 3560719.3 3530836 8052849645 7981002.7 7977600 17924469.3	Run 3	3556479	3570346	8052903192	7981856	7974848	17892672	2967433	3639348	8476975	1634780	927135	22582557
	Average	3560719.3	3530836	8052849645	7981002.7	0092262	17924469.3	3387651.33	3525232.7	8576056	1458289	876892.33	22885434

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Table

	FPGA (Alt	era Stratix V)	GPU (Nvidia GeForce GTX 680)	MIC (Intel Xeon Phi)
	Kernel 2	Kernel 2	Kernel 2	Kernel 2
	(Original)	(loop unrolled)	(Original)	(Original)
Run 1	8052825491	4237224	17914624	8824323
Run 2	8052820252	4238754	17966112	8426870
Run 3	8052903192	4242463	17892672	8476975
verage	8052849645	4239480.333	17924469.33	8576056

Reference:

Last modified:

Revision:

8

## 4. Implementing a DAQ system on FPGA with OpenCL

We have established that it is very easy to use OpenCL with FPGAs and to achieve identical or better performance compared to other architectures, but FPGAs are capable of more than just acceleration. So the next question that came up was whether OpenCL can be used to implement other systems like DAQ. To evaluate the possibility of implementing a DAQ system using OpenCL, an existing design was taken up. The Adaptive Header Generator [1] is an existing module in DAQ flow for the LHCb experiment. The purpose of the Header Generator system is to packetize the streamed data by creating a meta-header by combining the header information of hundreds of small event datasets. The Source Emulator creates a pseudo data stream. It serves the dual purpose of being a synthesizable test bench for the Header Generator and at the same time can function as a standalone module that can be integrated into other systems if required. This is not a parallelizable problem. Therefore it is an ideal test case for exploring OpenCL for non acceleration applications on FPGAs.



Figure 5. Complete data flow from random seed for source emulator to the generation of the modified data stream and the header

The existing Header Generator and the Source Emulator modules were implemented in VHDL. Figure 1 shows the data flow of the DAQ system with the major sub modules. The functionality of these modules was captured in OpenCL kernels and implemented using Altera's OpenCL compiler. The following sections describe the challenges faced in implementing this and their solutions.

#### 4.1. Handling IO and moving data between kernels

The very first task in DAQ is to clock the data into the FPGA. The OpenCL standard was initially created to exploit the parallelism of the many cores found in devices like GPUs and those devices are only capable of accelerating parallelizable workloads. Also, the original OpenCL spec does not have a provision for a generic I/O mechanism outside of communication with the Host CPU. One other task is to communicate the data between various kernels. In the OpenCL specification, again keeping in mind devices like GPUs, the only way to move data was by means of global memory access. The latencies involved with memory access would be too high for DAQ applications with streaming inputs. To overcome these limitations and meet these requirements, channel extension as provided by Altera can be used. Channels are FIFO based structures that can be used to move data between:

• I/O  $\rightarrow$  Kernel

- Kernel  $\rightarrow$  Kernel (bypassing the Global Memory)
- Kernel  $\rightarrow$  I/O

Using channels, the movement of data signals such as Rand and Stream, as shown in figure 1, were modelled. The concept of channels is incorporated in the next OpenCL 2.0 specification as pipes.

#### 4.2. Bit level manipulation and non standard data width

As is common with Data Acquisition systems, there was a need for bit level manipulation and variables with non-standard widths. There was a need to access a 16 bit ushort variable in chunks of 11 and 5 bits as well as whole to implement an addressing logic as shown in figure 2.



Figure 6. Accessing a memory element in parts and in whole

his type of memory access is not possible in devices like GPUs and has to be accomplished in an indirect manner with CPUs. However, this is trivially accomplished on an FPGA as follows:

SIGNAL location : STD\_LOGIC\_VECTOR(15 DOWNTO 0) ; alias uByte\_pos : STD\_LOGIC\_VECTOR(4 DOWNTO 0) is location (4 downto 0); alias nLines : STD\_LOGIC\_VECTOR(10 DOWNTO 0) is location(15 downto 5);

This kind of packed representation can be accomplished by means of bit fields. This feature, although present in the C, is absent from the OpenCL specification. However Altera's OpenCL compiler supports bit fields as it makes perfect sense on an FPGA. This can be implemented in OpenCL as follows:

```
typedef union loc
{
    Struct
    {
        uchar uByte_pos :5;
        ushort nLines :11;
    };
    ushort location;
};
```

This not only makes writing and understanding the code easier, but also results in efficient hardware on the FPGA.

#### 4.3. Control Signals

Control signals are integral to any Data Acquisition system. In our design from figure 1, apart from the data signals that we modelled as channels, these are the remaining signals:

- Clock and Reset
- Different Valid Signals (Strm\_valid, Len\_valid, Strm\_fwd\_valid)
- Throttle/Feedback signals (slow/slow\_n)
- **4.3.1. Clock and Reset Signals.** Altera's OpenCL compiler internally takes care of the clocking and reset of the kernel logic as well as for the memory access and communication with the Host CPU. These are hidden from the user.
- **4.3.2.** Valid Signals. In the HDL implementation of the design, valid signals corresponding to the different data signals need to be explicitly created. However when the data signals are modeled as channels with the Altera's OpenCL extension, the compiler automatically creates a valid and stall signal corresponding to each channel. Hence these are also hidden from the user.
- 4.3.3. **Throttle/Feedback signals.** In DAQ systems dealing with streamed data, feedback signals are employed to convey congestion information from downstream to upstream modules. Using these signals, the upstream modules can stop or slow the data flow so as not to overflow the buffers. These signals are even more critical in systems such as the Header Generator where its own data source does not have any flow control but its data sink requires flow control. The 'slow' signal in figure 1 serves this purpose and is generated by modules downstream of the Header Generator. When the slow signal is active, the logic in the Header Generator drops events from the data stream in a controlled fashion. The feedback signals are by definition asynchronous to the system and their relevance is instantaneous in nature. Unlike data signals where every single datum transmitted needs to be captured and in the same order, in the case of the throttle signal, only the current value is needed and it is critical that the current value is always available. There is no mechanism to model these signals in OpenCL. The usage of channels in this scenario was considered but since channels operate in a synchronous manner and the writes and reads to a channel always need to be in a 1:1 ratio, it is not suitable. Moreover, the internal flow control of the channels would interfere with the custom flow control of the system. Since the throttle signal cannot be implemented currently in OpenCL, this has become a road block in the attempt to realize a DAQ system on FPGA with OpenCL.

#### 4.4. Section Conclusion: DAQ Implementation with OpenCL

To my knowledge, this is one of the first instances to explore using OpenCL for applications outside of acceleration workloads. Acceleration workload in this context will be something that is parallelizable to finish the computation faster. This is in contrast to a monolithic non-acceleration workload such as DAQ. It may have sub-modules that are pipelined, but beyond that there is little parallelization involved and nothing to be accelerated. While the current OpenCL specification and the Altera specific extensions do not support

this kind of usage, it is not impossible to add appropriate support. Allowing asynchronous channels and adding support for 'VHDL signals' or 'Verilog wires' as FPGA specific extensions to OpenCL will facilitate modelling of these kinds of requirements. Since the underlying hardware is an FPGA that supports these kinds of operations and also since the Altera compiler actually generates a Verilog representation of the system from the High Level OpenCL constructs, it should be straight forward to add these functionalities. Altera has been notified both of this inadequacy in their current compiler and its possible solution described above. It is also possible that there might be more features and functionalities required by DAQ applications that were not encountered in this test application.

Since this is a novel attempt, the performance of the DAQ system is hard to predict. There are various factors that affect the prior estimation of performance of such as system. Since the coding is done in OpenCL and that is converted to Verilog and then synthesized for FPGA by Altera's tools, the internal structures of the kernels are hidden from the user. There will also certainly be an overhead involved with the OpenCL-based design. Finally, unlike custom-designed memory interfaces, the use of an auto-generated memory hierarchy in OpenCL can introduce uncertainties in memory access. All of these can make it hard to estimate the performance. Nevertheless the ease of use and the ensuing massive gain in productivity this approach offers outweigh the limitations and warrant further investigation on these lines.

## 5. Conclusion

An evaluation of using OpenCL with FPGA has been completed. An implementation of a Data Acquisition system was attempted along with an implementation of an algorithm for acceleration. The idea behind implementing a DAQ system was to explore the possibility of using OpenCL for more than just acceleration. Many of the design elements needed to realize a DAQ system in OpenCL already exist, mostly as FPGA vendor extensions. Some of these extensions are also going into subsequent versions of the OpenCL specification. However a small number of elements are also missing, preventing one from fully realizing a complete DAQ system today. Since these missing elements have simple feasible solutions, they could also be implemented if the FPGA tool vendors so desire. Hence it might soon be possible to implement a complete DAQ system on FPGA using OpenCL. It still remains to be seen how such a system would perform compared to a custom implementation in VHDL/Verilog, but there definitely exists a case for OpenCL in this application due to the massive productivity gain and ease of use it offers. Also, since this is a software-based development flow, this enables even non FPGA experts to design, debug and maintain the code. While this approach relies on vender specific extensions to a large extent, portability of the code is not a major concern as these kinds of designs cannot be realized on other devices, such as GPUs and other accelerators, anyway.

As for using OpenCL to accelerate algorithms on FPGA, in the test case the FPGA performed better in one instance and much worse in the other. Further work is necessary to determine the exact reason. An optimized implementation for FPGA would be a truer measure of the performance but irrespective of whether the performance is higher or lower than other devices, one thing that cannot be denied is that OpenCL makes exploiting FPGAs for acceleration as easy as exploiting GPUs. That is a long way from the days of painstaking efforts to create a cycle accurate HDL design, functionally verifying it, debugging the design errors and fixing the timing violations to realize a working system. Even if FPGAs lag behind other devices in terms of raw performance figures, which are not always the case, they are usually still better when the metric of comparison is Performance/Watt. It has been shown that FPGAs can order of magnitude advantage in terms of Performance/Watt. Extracting more parallelism from the algorithm, creating an FPGA optimized implementation, investigating the huge drop in performance for some kernels and also accurate power profiling of the designs could be the direction of future work.

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