

ME 759: Project Report

Parallel Implementation of VLSI Gate Placement in CUDA

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December 21, 2015

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Abstract: It is critical that Electronic Design Automation algorithms explore the possibilities of using GPU computing for extensive time consuming applications. This paper focuses on implementing gate placement algorithms for obtaining optimal wire length using CUDA and comparing it with a CPU implementation. GPU is approximately 3900 times faster than CPU for a similar algorithm for larger benchmarks. Optimizing GPU implementation further by hiding memory access latency and using shared memory is approximately 6400 times faster than CPU. This paper lays a foundation for doing gate placement on GPU kernel, and provides a game changing paradigm in VLSI EDA.

1. INTRODUCTION

A modern Very-Large Scale Integration (VLSI) chip is extraordinarily complex with billions of transistors, millions of logic blocks, big blocks of memory, and routing to connect them all together. These chips must be designed by using abstraction and a sequence of electronic design automation (EDA) or computer aided design (CAD) tools to manage the design complexity. Each EDA tool takes an abstract description of the chip and refines it step-wise. Multiple EDA tools are used to achieve the final design as shown in Figure 1.1.



One of the steps in VLSI design flow is placing gates on the layout (grid). Placing connected gates closer to each other results in shorter wires, thereby reducing total wire length. This, in turn, reduces delay and power consumption [1].

Many of the problems that arise in EDA for VLSI, are NP-complete that require an exponentially expensive amount of time. The trends of EDA often require either heuristic solutions or partitioning into smaller tractable problems. Graphics Processing Units (GPUs) are being extensively used because of their high performance capabilities, especially in extensive time consuming, large data applications. Therefore, VLSI can greatly benefit from high parallelization of GPU computing [3]. This paper focusses on a case study of gate placement on GPU.

2. PROBLEM FORMULATION

Input: netlist (list of interconnected logic gates) and random gate placement on grid



Figure 2.1: c17 benchmark. The figure on top is the visual representation of the netlist of c17. The figure on the bottom left is the text representation of the same netlist. The figure on the bottom right shows how these gates are actually routed together. Gate 10 is connected to gate 11 because they share common input 3. Likewise, gate 10 is connected to gate 22 because the output of gate 10 feeds directly into gate 22.

Constraints: non-overlapping gates and time limit

Goal/Output: location of each gate for near-minimum total wire length



2. METHODS AND PROCEDURE



Parser: takes the list of each gate and stores into a hash map of gate to netlist *Hash map of gate to netlist:* shows all netlists (every gate's connected list of gates) *Fisher-Yates Shuffle:* linear runtime to shuffle the location of each gate

Initial Random Placement: initial starting point for CPU and each GPU kernel				
Memcpy: malloc every array, copy array data, and then copy the pointers				
Wire Length: used as a comparison measurement to determine which location is better				
Swapping: move gate from one location to another				
CPU: pick a gate, do sequential computation, and move gate to its optimal location				
GPU1: pick a gate, have each thread compute wire length at an available location, move gate to its				
optimal location				
GPU2: pick 2 non-connected gates, have each thread compute wire length at an available location for				
both gates, and move both gates to their optimal location				
GPU3: pick 2 non-connected gates, schedule more threads to compute wire length at an available location				
for each gate, and move both gates to their optimal location				
GPU4: repeat GPU3, but move the location of each gate into shared memory since each thread uses it to				
compute wire length				

Benchmarks: ISCAS '85 benchmarks circuits are combinational circuits distributed at the 1985 International Symposium on Circuits and Systems for comparing results in test generation. The ISCAS '85 circuits have been widely used in the research community as a basis for comparison [4].

Circuit Name	Circuit Function	Number of Gates
c17	small example	6
c432	27-channel interrupt controller	160
c499	32-bit SEC circuit	202
c880	8-bit ALU	383
c1355	32-bit SEC circuit	546
c1908	16-bit SEC/DED circuit	880
c2670	12-bit ALU and controller	1193
c3540	8-bit ALU	1669
c5315	9-bit ALU	2307
c6288	16-bit Multiplier	2406
c7552	32-bit adder/comparator	3512

 Table 3.1: ISCAS'85 Benchmarks

Wire length: Wire length is used as a criteria to determine which location is better. The total wire length is the sum of the wire length of each net. Half perimeter wire length (HPWL) [1] is used to estimate the wire length of each net.



Swapping: Swapping moves a gate to a different location. The swap will be committed if the wire length is shorter, otherwise, the swap will be reverted. When computing wire length for swaps, only the half perimeter wire length of changed nets are computed.



3.1 CPU Implementation

Select a gate, sequentially compute wire length for all available locations, and move gate to its optimal location.







3.2 GPU1 Implementation

Pick a gate, have each thread compute wire length at an available location, and move gate to its optimal location [2].







3.3 GPU2 Implementation

Pick 2 non-connected gates, have each thread compute wire length at an available location for both gates, and move both gates to their optimal location.







3.4 GPU3 Implementation

Pick 2 non-connected gates, schedule twice the number of threads (compared to GPU2 implementation) to compute wire length at an available location for each gate, and move both gates to their optimal location.

```
device doIterationOnGPU3(gateToMove, anotherGateToMove) {
      if (threadId < 2 × numAvailableLocation) {</pre>
            d globalMemory[threadId] = getPartialWirelengthIfMoved();
      }
      if (threadId == 0) {
            for both gateToMove G {
                  locationWithMinWireLength = location(G);
                  minWireLength = d_globalMemory[0]; // numAvailableLocation 2<sup>nd</sup> time
                  for every availableLocation L {
                        if (d globalMemory[L] < minWireLength) {</pre>
                              minWireLength = d globalMemory[L];
                              locationWithMinWireLength = L;
                        }
                  }
                  swap(location(G), locationWithMinWireLength);
            }
      }
Figure 3.10: Pseudo code for an iteration on GPU3.
```





3.5 GPU4 Implementation

Repeat GPU3, but move the location of each gate into shared memory since each thread uses it to compute wire length.

```
device doIterationOnGPU4(gateToMove, anotherGateToMove) {
      sharedMemory[] = locations[];
      if (threadId < 2 × numAvailableLocation) {</pre>
            d globalMemory[threadId] = getPartialWirelengthIfMovedWithSharedMemory();
      }
      if (threadId == 0) {
            for both gateToMove G {
                  locationWithMinWireLength = location(G);
                  minWireLength = d globalMemory[0]; // numAvailableLocation 2<sup>nd</sup> time
                  for every availableLocation L {
                        if (d globalMemory[L] < minWireLength) {</pre>
                               minWireLength = d globalMemory[L];
                               locationWithMinWireLength = L;
                         }
                  }
                  swap(location(G), locationWithMinWireLength);
            }
      }
Figure 3.12: Pseudo code for an iteration on GPU4.
```

4. SIMULATION RESULTS

As explained in the previous sections, one gate is moved to its optimal location in one iteration in CPU and GPU1 implementation. Therefore, comparing CPU time against GPU1 inclusive time is fair, and is shown in figure 4.1 for different benchmarks (1024 iterations).



As seen in figure 4.1, GPU1 implementation is faster than CPU implementation because computing the wire length for every available location is done in parallel. Depending on the size of the benchmark, GPU1 achieves speedup between 12x - 3,900x compared to CPU.

For CPU and GPU1 implementation, the time required for one iteration is the time required to find an optimal location for one gate, which should be approximately same for each iteration. In the case of GPU2, GPU3, and GPU4, each iteration finds an optimal location for two gates. Figure 4.2 analyzes the effect of runtime against the number of iterations for c432 benchmark.



As expected and seen in figure 4.2, the number of iterations increase linearly with runtime for all implementations. The change in the number of iterations for CPU is not noticeable because each CPU iteration takes much longer than a GPU iteration. GPU1 does more iterations than GPU2 in the same amount of time because each thread in GPU2 does more work than GPU1. GPU3 and GPU4 do more iterations than GPU2 by hiding memory access latency and using shared memory, respectively.

The GPU1 moves one gate whereas GPU2/3/4 moves two gates to their optimal location in one iteration. As a result, GPU2/3/4 is expected to achieve reduced wire length compared to GPU1. Figure 4.3 shows comparison of wire length against the number of iterations for GPU1 (moving 1 gate) and GPU2/3/4 (moving 2 gates) for different benchmarks.



Figure 4.4 shows comparison of wire length obtained from CPU and all different GPU implementations with respect to the runtime for c1355 and c1908 benchmarks. CPU is very slow compared to all GPU implementations, and therefore, wire length barely reduces.



As expected and seen in figure 4.4, performance improves with every GPU optimization from hiding memory latency to using shared memory. However, there is a slight deviation from this behavior where GPU1 gives better wire length at 512 ms in c1908; probably because GPU1 does more iterations and moved more crucial gates.

5. CONCLUSION

Gate placement determines the wire length, which in turn, determines the power consumption and delay. This paper proposes four GPU kernels in a case study of gate placement for VLSI EDA: 1) each thread computes wire length for 1 gate, 2) increase parallelization by having each thread compute wire length for 2 gates, 3) hide memory access latency by scheduling twice the number of threads to compute wire length for 2 gates, and 4) reduce memory latency with shared memory. The four GPU kernels respectively perform up to 3900x, 5000x, 6000x, and 6400x faster than CPU. This paper lays a foundation for doing gate placement on GPU kernel, and provides a game changing paradigm in VLSI EDA.

6. REFERENCES

- R. Rutenbar, "ASIC Placement," https://spark-public.s3.amazonaws.com/vlsicad/lecture_slides/9vlsicad-placer.pdf, University of Illinois, 2013.
- [2] A. Al-Kawam, H. Harmanani, "A Parallel GPU Implementation of the TimberWolf Placement Algorithm," In *Information Technology - New Generations (ITNG), 2015 12th International Conference on*, vol., no., pages 792-795, 13-15 April 2015.
- [3] G. Flach, M. Johann, R. Hentschke, and R. Reis, "Cell placement on graphics processing units," In *SBCCI '07: Proc. Annual Conference on Integrated Circuits and Systems Design*, pages 87–92, 2007.
- [4] M. Hansen, H. Yalcin, J. Hayes, "ISCAS High-Level Models," http://web.eecs.umich.edu/~jhayes/iscas.restore/benchmark.html, University of Michigan, 1999.