Run-Time Technique for Simultaneous Aging and Power Optimization in GPGPUs

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Introduction

Massively parallel architecture: > 1000 SPs

High performance

- >1 Tflop/s (double-precision)
- >4 Tflop/s (single-precision) streaming multiprocessor (SM)



Introduction

Power is the first-order constraint for GPUs

- Power of modern high-performance GPUs: ~250W
 - High energy consumption
 - High requirements of chip cooling techniques
 - Reliability problems

GPU	Year	Power
NVIDIA GTX580	2010	244 W
NVIDIA GTX690	2012	300 W
NVIDIA TITAN	2013	250 W
NVIDIA K40	2013	235 W
AMD 7970	2012	225 W
AMD 7990	2013	300 W

Introduction

>Another challenge of modern ICs: aging effect

- Negative bias temperature instability (NBTI): the major aging issue in nano-scale ICs
- 20%-30% performance degradation after 3 years @ 45nm, 32nm, 22nm [Roy, D&T 2013]



Motivation

Low utilization of compute resources when running memory-intensive/bandwidth-bound kernels



Compute resources often idle (waiting for memory)

The more SMs the better?



 Off-chip memory bandwidth is saturated, increasing SMs cannot improve performance

Motivation

- Power-gate some SMs when running memoryintensive/bandwidth-bound kernels
 - Power saving
 - NBTI recovery
 - Low overhead



- Key problem: what is the optimal number of SMs for a given kernel?
 - It depends on the inputs, cannot be obtained offline

Contributions

- A run-time framework for simultaneous aging and power optimization for GPGPUs
 - Observation: memory-intensive/bandwidth-bound kernels achieve the best performance with only a portion of SMs
 - The off-chip memory bandwidth is saturated
 - Method: shut down some SMs at run-time
 - A modified performance model is used to predict the optimal number of SMs online before executing a kernel
 - Effect: power reduction and aging mitigation

Our solution



Our solution

Performance model

• The bandwidth is not saturated



• The bandwidth is saturated



Our solution

Online optimization algorithm

Algorithm 1: Finding the optimal GPU configurations

Input: the kernel (PTX code), the problem size, number of threads, and GPU parameters: Bandwidth, f, GlobalMemLatency, CacheLatency, CacheMissRate

Output: optimal #SM (optSM), and SM assignment

1 Evaluate the execution cycles using maximum #SM, denoted by C_{max} ;

2 for k = (maximum #SM) to (minimum allowed #SM) do 3 Evaluate the execution cycles using k SMs, denoted by C_k 4 if $C_k \leq C_{max}$ then

$$optSM =$$

5

k:

6 if optSM ==maximum #SM then 7 for k = (maximum #SM) to (minimum allowed #SM) do 8 l if $C_k \leq (1 + \delta)C_{max}$ then 9 l optSM = k;

10 Read NBTI-induced per-SM V_{th} shift from the NBTI sensors;
11 Assign the optSM SMs with the lowest degradation rates to execute the kernel, other SMs are power-gated;

Find the optimal number of SMs through the performance model

Assign SMs with the minimum aging rate, power gate other SMs

Experimental setup

Benchmarks

- CUDA SDK example
- Rodinia [Che, IISWC'09]
- Real-world kernels

Performance and power evaluation: GPGPU-Sim [Bakhoda, ISPASS'09] with GPUWattch [Leng, ISCA'13]

NBTI evaluation: NBTI analytical model [Bhardwaj, CICC'06]

Temperature evaluation: Hotspot [Huang, ISPASS'09]

• For NBTI calculation

➤ Baseline: GPU (16 SMs) without power gating

Simulation results

Optimal #SM and analysis time

Table 2: Results of the optimization algorithm.

$\operatorname{benchmark}$	optimal $\#SM$	online analysis time (μs)
BSRT	7	3.1
\mathbf{FWT}	15	2.5
HIST	15	2.8
LU	12	2.2
RED	15	2.2
RNG	11	2.1
\mathbf{RSRT}	8	2.5
SCPR	14	2.7
\mathbf{MT}	15	2.6
VAD	9	2.3
GAUS	13	3.0
PATH	15	2.8
HTSP	15	2.8
NN	15	2.5

Simulation results

- Performance degradation: < 1%</p>
 - Caused by shutting down some SMs and the online optimization algorithm
- Power reduction: 19%
- Energy reduction: 18%
- Reduction in NBTI-induced Vth shift: 34%

Simulation results

Our technique is implemented at run-time, it can handle different problem sizes

$\operatorname{input}_{\operatorname{size}}$	$\substack{ \text{optimal} \\ \#SM }$	$\begin{array}{c} {\rm normalized} \\ {\rm execution \ time} \end{array}$	NBTI mitigation	power saving	$\begin{array}{c} \text{energy} \\ \text{saving} \end{array}$
$\begin{array}{c} 1000 \\ 2000 \\ 3000 \\ 4000 \\ 5000 \end{array}$	$egin{array}{c} 4 \\ 7 \\ 10 \\ 12 \\ 15 \end{array}$	$\begin{array}{c} 0.804 \\ 1.016 \\ 0.988 \\ 1.046 \\ 1.003 \end{array}$	56.9% 54.9% 49.1% 44.7% 27.3%	$\begin{array}{c} 81.9\% \\ 63.8\% \\ 39.2\% \\ 28.5\% \\ 4.8\% \end{array}$	$\begin{array}{c} 85.4\% \\ 63.2\% \\ 40.0\% \\ 25.2\% \\ 4.5\% \end{array}$

Table 3. Results of PATH under different input sizes.

Table 4: Results of VAD, under different input sizes.

$\operatorname{input}_{\operatorname{size}}$	$_{\#\rm SM}^{ m optima}$	normalized execution time	NBTI mitigation	power saving	energy saving
$5000 \\ 10000 \\ 30000 \\ 50000$	5 7 9 9	$\begin{array}{c} 0.992 \\ 1.027 \\ 1.015 \\ 1.016 \end{array}$	54.0% 53.7% 48.2% 48.3%	$\begin{array}{c} 64.2\%\ 44.6\%\ 35.0\%\ 36.5\%\end{array}$	$64.4\%\ 43.1\%\ 34.0\%\ 35.5\%$

Conclusions

- Memory-intensive/bandwidth-bound kernels do not need all the compute resources
 - Memory bandwidth is saturated when using a portion of SMs
- A predictive shutting down framework to perform power gating for SMs in GPUs
 - A modified performance model is used to predict the optimal number of SMs
 - Assign SMs with the minimum aging rate, power gate other SMs
 - NBTI mitigation and power reduction are both achieved

Thanks for your attention Q & A