Directive-based Programming Models for Scientific Applications - A Comparison

Rengan Xu, Sunita Chandrasekaran,
Barbara Chapman, Christoph F. Eick

WOLFHPC'12 in conjunction with SC12

November 16, 2012

Outline

- Motivation
- Related Work
- Overview of Directive-based Models
- Experiments and Results
- Conclusion and Future Work

Motivation

- GPUs have high compute capability in HPC, but programming these devices is a challenge
- Low-level models: CUDA, OpenCL
  - Language extension
  - Time-consuming to write and error-prone
- High-level models: PGI, HMPP, OpenACC
  - High level directives: simplify GPU programming
  - Hiding low-level details from the programmer - main goals of abstraction
  - Reduce learning curve and development time

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Related Work

- **hiCUDA, Mint**: automatically translate C code to CUDA code
- **CUDA-lite**: apply global memory optimization via annotations, but it needs separate CUDA kernel functions
- **OpenMPC, OMPCUDA**: source-to-source translation of OpenMP program to CUDA program

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Overview of Directive-based Models

HMPP: Hybrid Multicore Parallel Programming workbench

- Two main directives: codelet and callsite
  - Codelet: the function that will be offloaded to accelerator
  - Callsite: the place to call the codelet
- Region directive is the combination of codelet and callsite
- Different codelets can be grouped together to share data
- A set of directives to enhance code generation
- Support multi-GPUs programming

Overview of directive-based models

PGI Accelerator Programming Model

- A set of directives
  - **Compute directive** specifies a portion of the program to be offloaded to accelerator
  - **Loop mapping directive** maps loop parallelism in a fine-grained manner. Two level parallelism: parallel and vector
  - **Data directive** is used to optimize data transfer
- Runtime library routines
- Environment variables

Overview of directive-based models

OpenACC

- Establishes a standard for directive-based accelerator programming
- Contains directives, runtime library routines and environment variables
- Similar to PGI accelerator programming model
- Two types of compute directives: "parallel" and "kernels"
- Three levels parallelism: gang, worker and vector

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Experimental Setup

- Evaluate HMPP, PGI and OpenACC for three scientific applications
- GCC 4.4.7 for all sequential programs as well as for HMPP host compiler, -O3 optimization flag

Table: Specification of experiment machine

Item	Description
Architecture	Intel Xeon x86_64
Cores	16
CPU frequency	2.27GHz
Main memory	32GB
GPU Model	Tesla C2075
GPU cores	448
GPU clock rate	1.15GHz
GPU global & constant memory	5375MB & 64K
Shared memory per block	48KB

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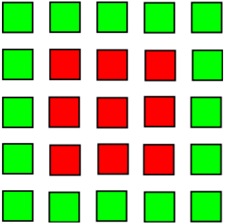
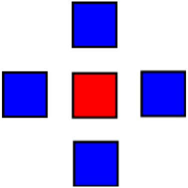
2D Heat Conduction

- Formula:

$$\frac{\partial T}{\partial t} = \alpha(\frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2})$$





2D Heat Conduction

- The kernel that does temperature updating is executed on GPU
- Optimizations
  - Loop collapse in kernel region
  - Data transfer optimization: make pointer swapping operation occur only in GPU
  - Mirror directive in HMPP
  - Deviceptr in PGI and OpenACC
  - Disable FMA to maintain same computation strategy in different implementations

2D Heat Conduction

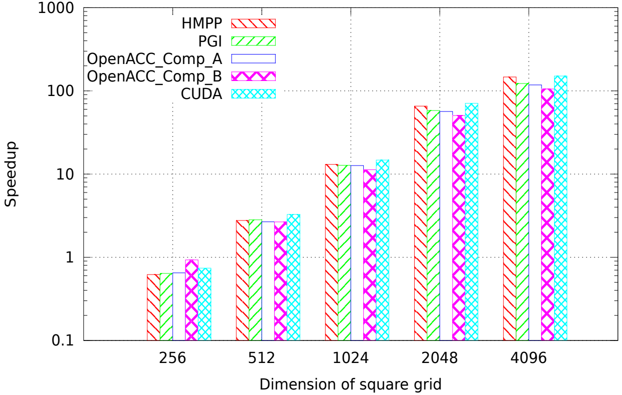


Figure: 2D Heat Conduction Speedup

FDK Algorithm

FDK: Feldkamp-Davis-Kress

- CT is widely used in medical industry to produce tomographic image of specific area of human body
- FDK is one of the popular 3D-object reconstruction techniques used in CT
- Complexity: $O(N^4)$, where N is the number of detector pixels in one dimension
- Implementation:
  - Code is restructured so that the outmost three loops are tightly nested and collapsed
  - The innermost loop is sequentially executed by every thread
  - Data transfer optimization to remove unnecessary data transfer
- Data: 3D Shepp-Logan head phantom data
- Input: 300 detected images and the resolution of each image is 200*200
- Output: 200*200*200 reconstructed cube

FDK Algorithm

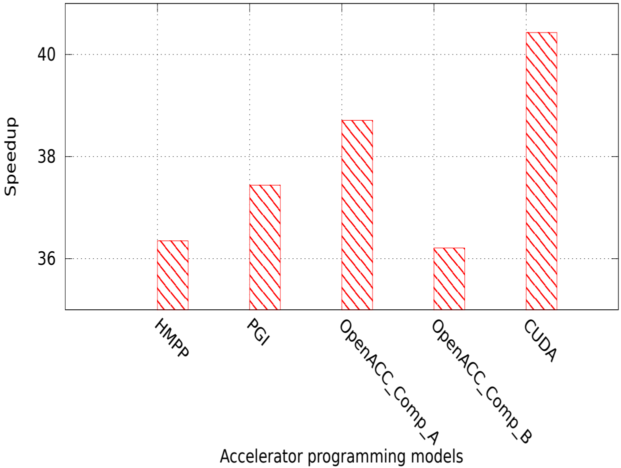


Figure: FDK Speedup with Different Models

CLEVER Algorithm

CLEVER: CLustEring using representatiVEs and Randomized hill climing

- A prototype-based clustering algorithm that seeks for clusters maximizing a plug-in fitness function
- It constructs clusters by seeking an optimal set of representatives one for each clusters; clusters are then created by assigning objects in the dataset to the closet cluster representatives.

CLEVER Algorithm

Implementation:

- Code is converted from C++ to C for better compilation
- Profiling result shows the most time consuming part is the part that assigns objects to the closet representative which computes and compares a lot of distances
- The user-defined structure of dataset and the pointer operation are too complicated to be parsed by compiler. So the code needs to be restructured.
- The whole dataset is read only, so it will stay in GPU global memory during execution

CLEVER Algorithm

Table: L10Ovals Dataset Characteristics

Item	Description
Data size	335,900 objects
Attributes	$<$x, y, class label$>$
Distance Function	Euclidean Distance
Plug-in Fitness Function	Purity:
	Percentage of objects belonging
	to the majority class of
	the cluster

Table: Earthquake Dataset Characteristics

Item	Description
Data size	330,561 objects
Attributes	$<$latitude, longitude, depth $>$
Distance Function	Euclidean Distance
Plug-in Fitness Function	High Variance:
	Measures how far the objects in
	in the cluster are spread
	out with respect to earthquake depth

CLEVER Algorithm

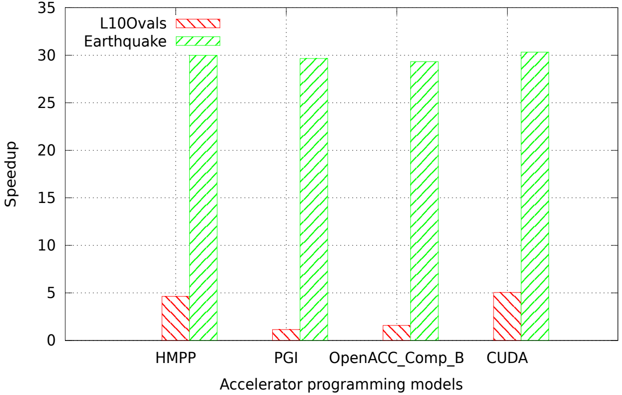


Figure: CLEVER Speedup with Different Models

Summary

Table: Time(in sec) consumed by serial, CUDA, HMPP, PGI and OpenACC versions of the code, only for most time-consuming dataset

Applications	Serial	CUDA	HMPP	PGI	OpenACC	
					A	B
2D Heat	8922.81	59.13	60.78	72.74	75.65	84.76
FDK	363.50	8.99	10.40	9.71	9.39	10.04
CLEVER	116.15	23.04	25.08	101.51	-	73.31

Conclusion and Future Work

- Conclusions:
  - High-level models provide a high-level abstraction by hiding most of the low-level complexities of the GPU platform
  - The performance is highly dependent on the application characteristics.
  - Directive-based models can achieve around 80% and sometimes more than 90% performance of CUDA code
  - OpenACC is still being constructed and may require fine tuning
- Future Work:
  - Multi-GPUs support in OpenACC
  - Add more loop optimization clauses in OpenACC

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