POLITECNICO DI MILANO



DIPARTIMENTO DI ELETTRONICA, INFORMAZIONE E BIOINGEGNERIA



DRuiD: Designing Reconfigurable Architectures with Decision-making Support

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Introduction and Motivation

Heterogeneous and reconfigurable architectures: – Coupling General Purpose Processors (GPPs) with reconfigurable hardware

Accelerate computational intensive kernels using HW

Application FPGA Bare Metal

The considered baseline design approach:
An application implementation is available in SW
Some kernels shall be ported to HW

Automatic Mapping Approach

- Conventional partitioning and mapping approaches in literature:
 - Kernels have one or more costs (e.g. execution time and area)
 - Assume kernel costs are known
 - Map to minimize the costs and fit in the constraints



Automatic Mapping Approach

Area

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Considering the application is available in SW Application

h.Vex. time

- The kernels must first be ported to HW
 - High level synthesis tools help (e.g. dwarv):
 - Restrictions on the C code
 - Cleanup the code

Are kernel costs known?

SW ex. time

- Some manual optimization
- Time consuming
- Error prone

Kernel id

K1

K2

КЗ

Compiler

source C code

Practical Mapping Approach

SW ex. time	htt ex. time	Area	Kernel id	
2	1	2	K1	
4	4	2	К2	
6	4	4	КЗ	

When porting an application to a heterogeneous and reconfigurable platform:

- Analyze the application:
 - Which kernel is expensive in SW?
 - Which kernel is suitable for HW?
 - Computational intensive?
 - Inherently sequential?

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Application

source C code

Decision Making Support

- Given the application source C code
- An expert system
 - Given a parametric representation of a kernel
 - Classifies the kernel
 - Learning the behavior of a set of known training kernels



Kernel Representation

- Static Code Analysis (SCA)
 - Instruction types
 - Control flow
 - Data flow
 - Variable scope and location
 - Pin based dynamic profiling, Microarchitectural Independent Characterization (MICA)
 - Instruction types
 - Instruction level parallelism
 - Memory and register access pattern
 - Branch predictability

Metrication Static

Code

Analysis

Dynamic Profiling

Kernel

SW

metrics

Training Overview



• Random Forest (RF):

metri

- Many decision trees are trained
- More robust than a single *decision tree*

Reduce the SW metrics by using a Genetic Algorithm (GA)

Source	Group name and acronym	Number of metrics	
SCA	Instruction type (IT)	45	
	Control flow (CF)	18	
	Data flow (DF)	15	
	Variables scope and location (VSL)	14	
MICA	Instruction type (IT)	12	
	Instruction level parallelism (ILP)	4	
	Memory and register access pattern (MRAP)	66	
	Branch predictability (BP)	15	
Total		189	

Training (GA + RF)

• A GA individual identifies the SW metrics to use



- A RF is trained on the reduced SW metric vector
- GA evolves a population of RFs to:
 - Maximize RF accuracy
 - Minimize the number of metrics

Prediction and Query

- A RF is a collection of *decision trees*
- For a given kernel, each tree votes either for FPGA or for GPP mapping
- Majority voting is used
- How modifications on the SW metrics impact on votes?



Experimental set up

- Target architecture is a Xilinx ml510 board
- The GPP is a **PowerPC**
- The reconfigurable HW is a Virtex5 FPGA
- 97 kernels taken from different sources (MediaBench, MiBench, CHStone, ...)
- Delft workbench toolsets:
 - C to VHDL using *dwarv*
 - FPGA logic area estimation from C using Quipu

Model Accuracy

- Probability of a kernel predicted as FPGA-accelerated to be truly accelerated (TAcc)
- Probability of a kernel predicted as NON FPGA-accelerated to be truly nonaccelerated (TNAcc)

Probability [%]

- Comparing different expert systems:
 - Random
 - Decision tree using SCA & MICA
 - RF using MICA metrics
 - RF using SCA metrics
 - RF using SCA and MICA



Case Study

- Susan edge application from automotive MiBench
- RF suggests not to use the FPGA due to non local memory

```
susan_principle (unsigned char *in, int *r, char *bp, int max_no, int x_size, int y_size) {
  int i, j, n,x;
  unsigned char *cp;
  unsigned char cU[3], cC[3], cD[3]; // Cache registers
  for (i=1; i < y_size_{-1}; i++)
    for (x=0; x<3; x++) // Cache data into registers
     cU[x] = in[(i-1) * x_size + x];
     cC[x] = in[(i) * x_size + x];
     cD[x] = in[(i+1) * x_size + x];
    for (j=1; j < x_size - 1; j++)
      n = 100;
      cp=bp + cC[1]; // Register read center
      n+=*(cp-cU[0]); // Register read left
      n+=*(cp-cU[1]); // Register read up
      n+=*(cp-cU[2]); // Register read up right
      n+=*(cp-cC[0]); // Register read left
      n+=*(cp-cC[2]); // Register read right
      n+=*(cp-cD[0]); // Register read down left
      n+=*(cp-cD[1]); // Register read down
      n+=*(cp-cD[2]); // Register read down right
      // Shift registers
     cU[0] = cU[1]; cC[0] = cC[1]; cD[0] = cD[1];
     cU[1] = cU[2]; cC[1] = cC[2]; cD[1] = cD[2];
     cU[2] = in[(i-1) * x_size + j+2]; // Mem read next up
     cC[2] = in[(i) * x_size + j+2]; // Mem read next
     cD[2] = in[(i+1) * x_size + j+2]; // Mem read next down
      if (n<=max no)
```

 $r[i * x_size + j] = 730 - n;$

Original version (3.96x speedup)

Conclusions

- We proposed a decision making support for the design of heterogeneous platforms
- A Random forest classification system is capable to learn what are the characteristics that make a kernel suitable for different computational elements
 - Given an architecture composed of a PPC and a Virtex5
 FPGA, the proposed methodology identifies the best
 computational element the 90% of the times



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