A Polynomial-Time Custom Instruction Identification Algorithm Based on Dynamic Programming

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### Outline

Introduction

**Problem Statement** 

Algorithm

Experiments and Results

Conclusion

Ready-made general-purpose processor with user-defined instructions for specific applications

- More flexible and easier to design than ASICs
- Higher performance and lower power consumption than GPP

# Configurable Processor



Optional FIFO, Memory, and Other Logic

Custom Instruction Logic of Nios II Processor

Ready-made general-purpose processor with user-defined instructions for specific applications

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Problem: How can we decide what to implement?

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#### Architectural constraints

- The number of inputs and outputs
- Types of operations that can be used in the custom functional unit

```
b = x + 1:
c = x - 1:
for (a = 0; a < 20; ++a) {
  t = a + b;
  u = a - c;
  d = (t * u) \& 0x000f;
  e = (t * u) \& 0x00f0;
  f = (t * u) \& 0x0f00;
  g = (t * u) \& 0xf000;
}
y = d + e + f + g;
```

#### CI Identification Flow

- 1. Select a kernel
- 2. Convert it into a DFG
- 3. Find the best CI



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Formal definition of the problem is as follows:

### Single Custom Instruction Identification Given a graph *G*, find a convex cut *S* that maximizes M(S)under the constraints $|IN(S)| \le N_{in}$ and $|OUT(S)| \le N_{out}$ .

- G: a DAG which denotes the data flow of a basic block
- ► S: a subgraph of G
- IN(S), OUT(S): inputs and outputs of a cut S
- M(S): user-defined function for evaluating a cut

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- Integer linear programming (K.Atasu, CODES+ISSS'05)

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• Too much time is needed for large dataflow graphs.

Nonoptimal solution with lower time complexity

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- The solution may not be optimal.
- Only connected cuts can be selected where disconnected cuts give better performance improvement in general.

Top-down dynamic programming with single cut identification algorithm (branch and bound with pruning)

- Solutions of subproblems are stored in a memoization table
- The stored solution is used instead of enumeration if avaliable

But, how can we guarantee that constraints are still satisfied even if we use stored solutions?

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Convexity constraint is violated when we add a vertex that has a path to an input which

- 1. is a follower vertex of S, or
- 2. has at least one includable ancestor that is a follower vertex of *S*.



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We call such inputs as watcher inputs.



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Solution

$$|\mathsf{IN}(S)| = |\mathsf{IN}_{\mathsf{w}}(S)| + |\mathsf{IN}_{\mathsf{nw}}(S)|$$



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#### Solution

*v* is an output if and only if it has at least one outside successor. We call an input with no outside successor as a **dedicated input**. Therefore,

$$|\mathsf{OUT}(S')| = egin{cases} |\mathsf{OUT}(S)| + 1 & v 
otin \mathsf{IN}_\mathsf{d}(S) \ |\mathsf{OUT}(S)| & \mathsf{otherwise} \end{cases}$$



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### Solution

When the last successor of an input is added to the cut, the input becomes dedicated unless it already has at least one outside successor (**permanently undedicated inputs**).



In short, I/O and convexity constraints can be checked with following properties when we inserting a follower vertex v to the convex cut S. (a **representative tuple**)

 $t(S) = (\mathsf{IN}_\mathsf{w}(S), |\mathsf{IN}_\mathsf{nw}(S)|, \mathsf{IN}_\mathsf{pu}(S), \mathsf{IN}_\mathsf{d}(S), |\mathsf{OUT}(S)|, \mathsf{v}_\mathsf{last}(S))$ 

Moreover, we found a function F for the following relation:

 $t(S \cup \{v\}) = F(t(S))$ 

Therefore, we can conclude the following.

### Corollary

When constructing a bigger convex cut  $S' = S \cup \{v\}$  from a convex cut S by adding a vertex in the pre-determined traversal order, the constraint on the number of inputs, outputs, and convexity of S' can be fully determined by only the following properties:  $IN_w(S)$ ,  $|IN_{nw}(S)|$ ,  $IN_{pu}(S)$ ,  $IN_d(S)$ , |OUT(S)|, and  $v_{last}(S)$ .

Thus, we can safely use stored solutions for all cuts with same representative tuple.

For 
$$S_1 = \{1, 5\}$$
,  
 $IN_w(S_1) = \{6, 7\} \quad |IN_{nw}(S_1)| = 0$   
 $IN_d(S_1) = \{6, 7\} \quad IN_{pu}(S_1) = \emptyset$   
 $|OUT(S_1)| = 2 \qquad \nu_{last}(S_1) = 5$ 



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If the best cut is  $S'_1 = \{1, 5, 6, 7\}$ , store  $S'_1 - S_1$  into the memoization table with a key k, where

$$\begin{split} k &= (\mathsf{IN}_\mathsf{w}(S_1), |\mathsf{IN}_\mathsf{nw}(S_1)|, \mathsf{IN}_\mathsf{d}(S_1), \\ & \mathsf{IN}_\mathsf{pu}(S_1), |\mathsf{OUT}(S_1)|, \mathsf{v}_\mathsf{last}(S_1)) \end{split}$$



For 
$$S_2 = \{2, 5\}$$
,  
 $IN_w(S_1) = \{6, 7\} \quad |IN_{nw}(S_1)| = 0$   
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We can use the stored solution from  $S_1$  due to the corollary. Therefore,

$$S_2' = S_2 \cup \{6,7\} = \{2,5,6,7\}$$



Branch-and-bound search can be visualized as a binary tree.



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- 1. Total search space
- 2. Pruned by K. Atasu's algorithm (with  $N_{in} = 8$ ,  $N_{out} = 4$ )
- 3. Used memoized solutions (our approach)

How about optimality?

### Theorem

The single cut identification problem has optimal substructure if  $M(S \cup S') = M(S) + M(S')$ .

Therefore, the algorithm is optimal for  $M(S) = \sum_{v \in S} s_v$ . However,

$$\mathsf{M}(S) = \sum_{v \in S} s_v - \lceil L \rceil$$

is used in general. In this case, the proposed algorithm may give an approximated solution.

The upper bound for the size of the memoization table:

$$O\left(|V|^{N_{\mathsf{in}}} \cdot (N_{\mathsf{in}}^{N_{\mathsf{in}}})^2 imes N_{\mathsf{in}} imes |V|^2 imes N_{\mathsf{out}}
ight)$$

The time complexity for processing each item:

$$O(N_{in} + |V| + 1)$$

Therefore, the overall time complexity of our algorithm is

$$O\left(|V|^{N_{\rm in}+3}\cdot N_{\rm in}^{3N_{\rm in}}\cdot N_{\rm out}
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Note that two previous optimal algorithms have  $O\left(2^{|V|}\right)$  time complexity.

### Experiments

We compared the execution time of the proposed algorithm (**memoized**) to that of the K.Atasu's single cut identification algorithm (**exhaustive**).

### Settings

- Merit function is defined as a difference between software and hardware latency.
- The size of the memoization table is limited to one million items. (consumes roughly 500MB memory)

## Synthetic Graphs

The following result is for randomly generated dataflow graphs with 87 to 963 vertices.



All solutions obtained by **memoized** were optimal.

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## Real World Applications from MiBench

Name	V	I/O	exhaustive	memoized	Speedup	$d_{\rm SW}^{\dagger}$	$d_{\rm CI}^{\dagger}$
SHA	38	4/2 8/4	0.032s 3.696s	0.016s 1.083s	2.00 3.41	50	37 13
JPEG*	92	4/2 8/4	0.120s 69.67s	0.020s 4.460s	6.00 15.62	164	144 131
ADPCM*	133	4/2 8/4	0.411s 89.71s	0.091s 8.952s	4.52 10.02	220	193 152
MAD	137	4/2 8/4	1.125s 311.5s	0.264s 71.91s	4.26 4.33	337	326 304
SUSAN	197	4/2 8/4	0.261s 216.8s	0.055s 23.26s	4.75 9.32	525	515 503
AES	247	4/2 8/4	1.271s 183.0min	0.274s 30.24min	4.64 6.05	431	414 392
Blowfish	414	4/2 8/4	1.433s 71.24min	0.280s 12.35min	5.12 5.77	219	212 185

\* disconnected graph

<sup>†</sup> execution cycle of the basic block without ( $d_{SW}$ ) and with ( $d_{CI}$ ) a custom instruction

## Real World Applications from MiBench



## Conclusion

We proposed a polynomial-time algorithm for custom instruction identification.

- The correctness of the algorithm is proved theoretically.
- The algorithm gives an optimal solution for generally used merit function with very high probability.
- The algorithm is significantly faster than the previous approach.