Chapter 3-1: Programs

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High Performance Embedded Computing

Topics

- Code generation and back-end compilation.
- Memory-oriented software optimizations.

Embedded vs. general-purpose compilers

- General-purpose compilers must generate code for a wide range of programs:
 - No real-time requirements.
 - Often no explicit low-power requirements.
 - Generally want fast compilation times.
- Embedded compilers must meet real-time, low-power requirements.
 - May be willing to wait longer for compilation results.







Code generation steps



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twig model for instruction selection

- twig models instructions, programs as graphs.
- Covers program graph with template matching of instruction graph.
 - Covering can be driven by costs.
 - Use of annotations, such as execution time or energy consumption



twig instruction models

- Rewriting rule:
 - Replacement <- template {cost} = action</p>
- Dynamic programming can be used to cover program with instructions for tree-structured instructions.
 - Must use heuristics for more general instructions.



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Register lifetimes

- Variable liveness
- V1 and v3 can be assigned to the same registers; similarly, v2 and v4 can be assigned to the same register.
- They are never live at the same time.



v1 <= i1; v2 <= v1 + 1; v3 <= v2

v4 <= v3 - 1; Code

- i2;

Register lifetimes



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Conflict graph and Clique covering

- Cliques in graph describe registers.
 - Clique: every pair of vertices is connected by an edge.
- Cliques should be maximal.
- Clique covering performed by graph coloring heuristics.



Code placement

- Place code to minimize cache conflicts.
 - Two memory blocks can be mapped into a cache line.
- Possible cache conflicts may be determined using absolute addresses
- May require blank (unused) areas in program.



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Linker and Loader

- The linker put together several independently compiled parts into a complete program.
- The loader takes relocatable machine code and alter the addresses, putting the instructions and data in a particular location in memory.

Hwu and Chang

- Analyzed traces to find relative execution times.
- Inline expanded frequently used subroutines to eliminate function call overhead.
- Placed frequently-used traces in the program image by using greedy algorithm.

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McFarling procedure inlining

- Estimated number of cache misses in a loop:
 - $s_1 = effective loop body size.$
 - s_b = basic block size.
 - f = average instruction execution frequency of block.
 - M₁ = number of misses per loop instance.
 - I = average number of loop iterations.
 - \Box S = cache size.
- Estimated new cache miss rate for inlining;
- Used greedy algorithm to select functions to inline.

$$s_l = \sum s_b \min(1, f),$$

$$M_l = \max(0, l-1)\max(0, s_l - S),$$

Pettis and Hansen

- Profiled programs using gprof.
- Put caller and callee close together in the program, increasing the chance they would be on the same page.
- Ordered procedures using call graph, weighted by number of invocations, merging highly-weighted edges.
- Rearranged if-then-else code to take advantage of the processor's branch prediction mechanism.
- Identified basic blocks that were not executed by given input data; moved to separate processes to improve cache behavior.

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FlexWare ASIP programming environment



Memory-oriented optimizations



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- Memory is a key bottleneck in many embedded systems.
 - Performance
 - Energy
- Memory usage can be optimized at any level of the memory hierarchy.
 - Various techniques have been developed
 - Recently, optimization for scratch pad memory is developed
- Optimization can target data or instructions.
- Global flow analysis can be particularly useful.
 - Most of embedded systems are composed of many subsystems.
 - Buffers between the subsystems must be carefully sized.

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Loop transformations

- Some optimization are applied early during compilation without detailed knowledge of the target hardware.
 - Try to expose parallelism that can be used by later stages.
- Loop-carried dependency

for (i=0; i<N; i++)
 c[i] = a[i] + b[i];
Fully parallelizable</pre>

for (i=1; i<N; i++)
c[i] = a[i] + c[i-1];
Loop-carried dependencies</pre>

Loop transformations

- A loop nest has loops enclosed by other loops.
- A perfect loop nest has no conditional statements.
- An imperfect loop nest has conditional that cause some statements in the nest to not be executed in some cases.

for (i=0; i<N; i++)
for (j=0; j<M; j++)
for (k=0; k<L; k++)
c[k] = a[i][j] * b[k];
Perfect loop nest</pre>

for (i=0; i<N; i++) for (j=0; j<M; j++) if (i != j) for (k=0; k<L; k++) c[k]= a[i][j] * b[k]; Imperfect loop nest

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- Loop permutation changes order of loops.
- Index rewriting changes the form of the loop indexes.
- Loop unrolling copies the loop body.
- Loop splitting creates separate loops for operations in the loop body.
- Loop merging combines loop bodies.
- Loop tiling splits a loop into a nest of loops, with each inner loop working on a small block of data
- Loop padding adds data elements to change cache characteristics.

Polytope model

- Commonly used to represent and manipulate the data dependencies in loop nests.
- Loop transformations can be modeled as matrix operations:



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Loop permutation and fusion

for (j=0; j<M; j++)
for (i=0; i<N; i++)
 x[i][j] = a[i][j] * b[j];
Original loop nest</pre>

for (i=0; i<N; i++)
 for (j=0; j<M; j++)
 x[i][j] = a[i][j] * b[j];
After loop permutation</pre>

for (i=0; i<N; i++)
 for (j=0; j< j j++)
 x[i][j] = a[i][j] * b[j];
 After loop fusion</pre>

Loop fusion

```
for i=0, N
for j=0,M
A[i,j]=C[i-2,j+1];
endfor
for j=0, M
B[i,j]=A[i,j+1]+A[i,j]+C[i-1,j];
endfor
for j=0, M
C[i,j]=B[i,j]+A[i,j+2]+A[i,j+1];
endfor
endfor
```

(a) The original loop with fusionprevention dependencies.

```
for i=0, N

A[i,0]=C[i-2,1];
A[i,1]=C[i-2,2];
B[i,0]=A[i,0]+A[i,1]+C[i-1,0];
for j=0, .M-2

A[i,j+2]=C[i-2,j+3];
B[i,j+1]=A[i,j+2]+A[i,j+1]+C[i-1,j+1];
C[i,j]=B[i,j]+A[i,j+1]+A[i,j+2];
endfor

B[i,M]=A[i,M]+A[i,M+1]+C[i-1,M];
C[i,M-1]=B[i,M-1]+A[i,M]+A[i,M+1];
C[i,M]=B[i,M]+A[i,M+1]+A[i,M+2];
endfor
```

(b) The fused loop after transformation.

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Kandemir et al. loop energy experiments

ABSTRACT

High-level compiler optimizations have been widely used to achieve speedups on arry-based codes. Such optimizations are becoming increasingly important in embedded signal processing and multimedia systems. The focus of these optimizations has traditionally been on improving performance. Ho weverenergy constraints are of critical importance in battery-operated embedded devices. In this paper, we present an experimental evaluation of several state-ofthe-art compiler optimizations on energy consumption, considering both the processor core (datapath) and memory system. This is in contrast to many of the previous works that have considered them in isolation.

Program	Array Sizes	Miss Rate	Optimizations
adi hydro2d/fct nasa7/btrix nasa7/cholesky tomcaty	$\begin{array}{r} 100*100*2\\52*52\\100*100*100*5\\52*52\\100*100\end{array}$	$\begin{array}{c} 0.0979 \\ 0.0962 \\ 0.2063 \\ 0.1109 \\ 0.2403 \end{array}$	linear transforms, tiling loop fusion loop fusion loop fission scalar expansion

Table 1: Programs used in the experiments.

A C source benchmark is compiled by the SimpleScalar version of gcc, which generates SimpleScalar assembly codes. The SimpleScalar assembler gas and loader/linker gld produce SimplePower executables that can then be loaded into SimplePower main memory and executed by SimplePower core. In our study, we enhanced a source-to-source optimizer [4] to perform the various code transformation investigated. The simulator can be configured using the command line to set the caches parameters, output the pipeline trace cycleby-cycle, and dump the memory image. SimplePower provides the register file final status, total number of cycles in execution, number of transitions in on-chip buses, switch capacitance statistics for each pipeline stage, switch capacitance statistics for different functional units, and the total switch capacitance.

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Kandemir et al. loop energy experiments

In adi, the linear loop optimizations interchanged the order of two loops in the main nest in an attempt to obtain stride-one accesses in the innermost loop, thereby improving spatial locality. (The original version is denoted by orig and the tiled version is denoted by tile). When we enable tiling, the compiler tiled the innermost loop and hoisted the tile loop (i.e., the loop that iterates on tiles) to the outermost position. Note that in order to run this code standalone, we added a two-deep initialization nest (i.e., a nest that contains two nested loops). The linear transformation permuted this nest whereas tiling did not modify it due to its relatively small contribution to the overall performance.

	Core	Memory Energy				
	Energy	(\mathbf{J})				
	(J)	\downarrow	1-way	2-way	4-way	8-way
		1K	0.1604	0.0915	0.0794	0.0772
		2K	0.1159	0.0789	0.0756	0.0757
orig	0.0043	4K	0.1000	0.0763	0.0759	0.0760
		8K	0.0730	0.0681	0.0742	0.0766
		1K	0.1418	0.0630	0.0526	0.0468
		2K	0.0844	0.0493	0.0435	0.0436
loop	0.0054	4K	0.0609	0.0441	0.0439	0.0440
		8K	0.0378	0.0283	0.0231	0.0251
		1K	0.1404	0.0731	0.0729	0.0688
		2K	0.0942	0.0646	0.0674	0.0689
tile	0.0052	4K	0.0550	0.0426	0.0465	0.0457
		8K	0.0345	0.0228	0.0220	0.0221

Table 2: Energy consumption in adi.

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Kandemir et al. loop energy experiments

In the adi code, the number of memory accesses per computation is very high. This is because the it accesses threedimensional arrays using two-deep loop nests. Consequently, as shown in Table 2, the core power is very low compared to memory power for all cache configurations. An optimizing compiler can be very aggressive in applying potential optimizations such as tiling, if it can detect that the number of memory references per computation is very high. However, we note that applying tiling increases the core energy consumption.

In nasa7/btrix, in order to isolate the impact of loop fusion, we disabled other loop optimizations, and experimented with only original (orig) and fused (fuss) versions. When fusion is activated, the compiler fused two large one-dimensional (one-deep) loop nests into a very large loop. This example gives us the opportunity for observing the impact of loop fusion (in its extreme, when the resulting loop body gets very large and the chances for intra- and inter-array conflict misses in the data cache increase greatly) on power dissipation. In hydro2d/fct, we again measured the impact of fusion on power consumption using the original (orig) and the fused (fuss) versions. This time the compiler fused both initialization nests (three of them) as well as two main loop nests (each two-deep). In comparison to nasa7/btrix, the resulting loop bodies are not very large.

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	Core Energy	Memory Energy (J)				
orig	0.1565	* 1K 2K 4K 8K	$ \begin{array}{r} 8.4840 \\ 3.3221 \\ 1.6816 \\ 1.3291 \end{array} $	3.9372 2.3311 1.3939 0.9573	$\begin{array}{r} 2.8179 \\ 1.3897 \\ 1.1123 \\ 0.8942 \end{array}$	2.9734 1.2614 1.1155 0.8752
fuss	0.1748	1K 2K 4K 8K	9.4086 3.9100 1.8087 1.3887	$\begin{array}{r} 4.4788 \\ 2.5048 \\ 1.4712 \\ 0.9480 \end{array}$	$\begin{array}{r} 3.1901 \\ 1.4469 \\ 1.1003 \\ 0.8852 \end{array}$	$\begin{array}{r} 3.2580 \\ 1.2732 \\ 1.1033 \\ 0.8652 \end{array}$

Table 3: Energy consumption in nasa7/btrix.

	Core	Memory Energy				
	Energy	(J)				
	(J)	\downarrow^{\rightarrow}	1-way	2-way	4-way	8-way
		1K	0.0290	0.0117	0.0079	0.0079
		2K	0.0130	0.0069	0.0060	0.0054
orig	0.0008	4K	0.0086	0.0055	0.0054	0.0054
		8K	0.0066	0.0055	0.0055	0.0053
		1K	0.0277	0.0102	0.0073	0.0068
		2K	0.0095	0.0074	0.0061	0.0063
fuss	0.0006	4K	0.0069	0.0050	0.0050	0.0050
		8K	0.0057	0.0050	0.0050	0.0050

Table 4: Energy consumption in hydro2d/fct.

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In the next two examples, we evaluated the impact of loop fusion on core and memory system energy consumption. In nasa7/btrix, the loop fusion interferes with loop scheduling as the loop body becomes very large. This increases the core power (by 12%) as well as memory power (due to poor scheduling of memory operations) as shown in Table 3. Unfortunately, scalar replacement could not eliminate the large number of memory references. On the other hand, if the cache size is large or the associativity is high, scheduling memory operations becomes less critical (unless the cache is direct-mapped, in which case poor scheduling induces more conflict misses). For example, for a 4K, 4-way set associative cache, the fused version is marginally better than the original. In the hydro2d/fct case, the same optimization is more successful from the energy point of view (see Table 4). It reduces the core power as well as the memory system power by as much as 25%. The reduction in the memory power comes from reductions in the number of memory references rather than from hit/miss rate variations. Overall, we believe that, if applied judiciously, the loop fusion can reduce both the core and memory system power.

Catthoor et al. methodology

It	is for streaming systems such as multi-media
	Memory-oriented data flow analysis and model extraction, which analyzes loops to identify memory requirements.
	Global data flow transformations to improve memory utilization.
	Global loop and control flow optimizations to eliminate system-level buffers and improve data locality
	Data reuse decisions for memory hierarchy exploits caches to reduce energy consumption and improve performance
	Memory organization designs the memory systems and its ports
	In-place optimization use low-level techniques to reduce storage requirements
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Buffers

- Buffers mediate between subsystems
- Producers: subsystems that generate data
- Consumers: subsystems that consume data
- Buffers make sure that all data are delivered form the producer to the consumer
- The buffers must be sized properly

Buffer management

- Excessive dynamic memory management wastes cycles, energy with no functional improvements.
- IMEC: analyze code to understand data transfer requirements, balance concerns across program.
- Panda et al.: loop transformations can improve buffer utilization.
 - Reuse b more easily
 - Easier for pre-fetching
- Before: for (i=0; i<N; ++i) for (j=0; j<N-L; ++j) b[i][j] = 0; for (i=0; i<N; ++i) for (j=0; j<N-L; ++j) for (k=0; k<L; ++k) b[i][j] = a[i][j+k];
- After: for (i=0; i<N; ++i) for (j=0; j<N-L; ++j) b[i][j] = 0; for (k=0; k<L; ++k) closer

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Cache optimizations

- Strategies:
 - (Improve hit rate) rearrange data to reduce the number of conflicts.
 - rearrange data to take advantage of prefetching.

Need:

- □ Load map.
- Information on access frequencies.

Cache data placement

- Panda & Dutt: rearrange data to reduce cache conflicts. It is for scalar variables.
- Build a closeness graph for accesses by using the access patterns of the variables.
- 2. Cluster variables into cache-line sized units.
- 3. Build a cluster interference graph.
- 4. Use interference graph to optimize placement.



Memory Data Organization of Scalar Variables

- Assumption
 - scheduling and register allocation already performed
 - sequence of accesses to variables is fixed
- Steps
 - Build Closeness Graph
 - Group the variables into clusters of *L* words (*L*: cache line size)
 - Build a Cluster Interference Graph (CIG)
 - Assign memory locations to clusters

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Generate an Access Sequence



distance(u, v) = number of distinct variable nodes encountered on a path from u to v, or v to u (including u and v)

Memory Organization of Scalar Variables

Construct a Closeness Graph of the variables



Closeness Graph for loop bound = 3

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Grouping of Variables into Clusters

Procedure *PeformClustering* **Input:** CG(V, E) - Closeness Graph; L - Cache Line Size **Output:** Set *F* - Set of clusters of size *L* for each vertex *u* in *V* Find the sum of incident edge weights $S(u) = \sum_{v \in V} e(u, v)$ end for Let X = vertex set V. while $(X \neq \phi)$ do Let $u = vertex \ v \in X$ with maximum S(v)Create new cluster $C - \{u\}$ while (size of cluster $C \neq L$) and $(X \neq \phi)$ do Let x be the variable $\in X$ with maximum value for T. where $T = \Sigma_{u \in C, v \in X-C} e(u, v)$ -- *i.e.*, *x* is the variable with maximum sum $C = C \cup \{x\}; X = X - \{x\}$ -- of edge weights with nodes already in C end while **Set** $e(u, v) = 0 \quad \forall (u \in C) \text{ or } (v \in C)$ -- i.e., delete all edges connecting to vertices in cluster C just formed Update $S(v) \forall (v \in X)$ end while end Procedure

Cluster Interference Graph (CIG)

Procedure for generating the CIG

Procedure BuildCIG

Input: *A* - Variable Access Sequence; *F* - Set of Clusters Output: *CIG* - Cluster Interference Graph

Convert the Variable Access Sequence A into a Cluster Access Sequence by renaming each node u in the sequence by the cluster C, where $u \in C$. Create a node in CIG for each cluster in F.

Assign edge weight e(u, v) between nodes u and v = the number of times the access to cluster u and v alternate along the execution path.

end Procedure

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Cluster Interference Graph (CIG)

Memory Location Assignment

• The cost of a *memory assignment* :

 $MemAssignCost(CIG) = \sum_{x,y \in V(CIG)} e(x,y) \times P(x,y)$

where e(x,y) is the edge weight, and

P(x,y) = 1 if memory locations for x and y map into the same cache line 0 otherwise

- In order to minimize conflict misses, we need to solve the following Cluster Assignment problem:
 - Find an assignment of clusters in a CIG to memory locations, such that MemAssignCost (CIG) is minimized.

Memory Location Assignment

S(f) = 15, S(c) = 9, S(e) = 9, S(b) = 8, S(d) = 5, S(a) = 5

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Memory Location Assignment

- Procedure for assigning clusters to memory locations

Procedure AssignClusters

Input: *CIG(V,E)* - Cluster Interference Graph Output: Assignment of Clusters to Memory Locations

Sort the vertices of CIG in descending order of S(u)

-- S(u) is the sum of edge weights incident on vertex uLet X be this sorted list of vertices while $(X \neq \phi)$ do Create new page P in memory while (size of page P < k) and $(X \neq \phi)$ do u = head of list XAssign u to line i of page P, where cost(u, i) is minimum over $i=0 \dots k-1$ Delete u from Xend while end while end Procedure

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Memory Organization for Array Variables

Objective

- Minimizing data cache conflict misses
- The problem of clustering of variables to avoid compulsory misses is not relevant.

Steps

- Constructing the Interference Graph
- Memory Assignment to Array Variables

Constructing the Interference Graph

- If two arrays A and B are accessed repeatedly within a loop, then there is a possibility that accesses to A and B might cause conflict misses in the data cache.
- Procedure for building Interference Graph for arrays

Procedure *BuildArrayIG* Input: Code with array accesses Output: Interference Graph IG of arrays

Create a node *u* for every array *u* in the code Initialize edge weights e(u,v) = 0 for all *u*, *v* for all (innermost) loops *l* in the code **do** Let *L* be the loop bound of loop *l* Let *X* = set of all arrays accessed in *l* Update e(u, v) = e(u, v) + L for all $u, v \in X$ end for end Procedure

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Memory Assignment to Array Variables

 Interference Graph: edge weights contributed by loop bounds

Two memory locations X and Y will map into the same cache line in a directmapped cache with k lines (L words per line), if

 $\left(\left\lfloor \frac{X}{L} \right\rfloor - \left\lfloor \frac{Y}{L} \right\rfloor\right) \mod k = 0 \quad i.e., \quad (nk-1) < \frac{X-Y}{L} < (nk+1) \quad (4.1)$

Memory Assignment to Array Variables

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Memory Assignment to Array Variables

Cost function for expected number of conflicts

Function AssignmentCost

Input: *u* - array under test; *A* - proposed start address; Access Sequence; Array assignment already completed; *IG* - Interference Graph Returns: Expected number of cache conflicts for this assignment

Initialize cost = 0for all $v_i | e(v_i, u) \neq 0$, v_i already assigned -- *i.e.*, all assigned arrays that have an edge with u in IG for each loop (bound L) in which accesses to v_i and u occur w = no. of times control alternates between elements of v_i and u that map into the same cache line, using Condition (4.1) cost = cost + w * L -- w = 0 if there is no conflict end for return cost end Function

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Memory Assignment to Array Variables

Procedure for assigning addresses to arrays

```
Procedure AssignArrayAddresses
Input: IG - Interference Graph; k - number of cache lines
Output: Assignment of addresses to all arrays (nodes in IG)
  Address A = 0
  Sort nodes in IG in decreasing order of S(u) (sum of incident edge weights)
  Let the list of nodes be: v_0 \dots v_{n-1}
  for i = 0 ... n-1
     Initialize cost c = \infty
     min = 0
                   -- keeps track of cache line with minimum mapping cost
     for i = 0 \dots k-1
       if AssignmentCost(v_i, A+j) < c then
          c = AssignmentCost(v_i, A+j)
          min = i
       end if
     end for
     Assign address (A+min) to first element of v_i
     A = A + min + arraysize(v_i) -- updating A for next iteration
  end for
end Procedure
```

Memory Assignment to Array Variables

- This cost is equal to the expected number of cache conflicts with all arrays that have already been assigned.
- If the conflict condition does not resolve to a constant, then we conclude that the two arrays do not conflict.

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Scratch Pad Memory

Figure 1. (a) Block Diagram of Embedded Processor Configuration (b) Division of Data Address Space between SRAM and DRAM

Scratch Pad Memory

The accesses to Hist are data-dependent

char BrightnessLevel [512][512]; int Hist [256]; /* Elements initialized to 0 */ ... for (i = 0; i < N; i + +)for (j = 0; j < N; j + +)/* For each pixel (i, j) in image */ level = BrightnessLevel [i][j]; Hist [level] = Hist [level] + 1;

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