Fast Searches for Effective Optimization Phase Sequences

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Phase Ordering Problem

- A single ordering of optimization phases will not always produce the best code
  - different applications
  - different compilers
  - different target machines

Example

- register allocation and instruction selection
Approaches to Addressing the Phase Ordering Problem

- Framework for formally specifying compiler optimizations.
- Single intermediate language representation
  - repeated applications of optimization phases
- Exhaustive search?
- Our approach
  - intelligent search of the optimization space using genetic algorithm
Genetic Algorithm

A biased sampling search method
– evolves solutions by merging parts of different solutions

Flowchart:
- Create initial population of optimization sequences
- Evaluate fitness of each sequence in the population
- Terminate cond.?
- Perform crossover/mutation to create new generation
- Output the best sequence found

Y

N
Genetic Algorithm

- A biased sampling search method
  - evolves solutions by merging parts of different solutions

```
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Evaluate fitness of each sequence in the population

Terminate cond.?

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Genetic Algorithm

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1. Create initial population of optimization sequences
2. Evaluate fitness of each sequence in the population
3. Terminate cond.?
   - Y: Output the best sequence found
   - N: Perform crossover/mutation to create new generation
4. Repeat from step 2 if termination condition is not met.
Genetic Algorithm

- A biased sampling search method
  - evolves solutions by merging parts of different solutions

Create initial population of optimization sequences

Evaluate fitness of each sequence in the population

Terminate cond. ?

Perform crossover/mutation to create new generation

Output the best sequence found
Genetic Algorithm (cont…)

**Crossover**
- 20% sequences in each generation replaced

**Mutation**
- phases in each sequence replaced with a low probability
Genetic Algorithm (cont…)

C Source Function → Compiler → Assembly Function

Genetic Algorithm

candidate phases

best sequence
Experiments

- Performed on six mibench benchmarks, which contained a total of 106 functions.
- Used 15 candidate optimization phases.
- Sequence length set to 1.25 times the number of successful batch phases.
- Population size set to 20.
- Performed 100 generations.
- Fitness value was 50% speed and 50% size.
Genetic Algorithm – Results

- **bit count**
- **dijkstra**
- **fft**
- **jpeg**
- **sha**
- **stringsearch**
- **average**

Percentage improvement compared to the batch compiler:

- **Size**
- **Speed**
Our Earlier Work

Published in LCTES ’03

- complete compiler framework
- detailed description of the genetic algorithm
- improvements given by the genetic algorithm for code-size, speed, and 50% of both factors
- optimization sequences found by the genetic algorithm for each function
- Finding Effective Optimization Phase Sequences –
  http://www.cs.fsu.edu/~whalley/papers/lctes03.ps
Genetic Algorithm – Issues

- Very long search times
  - evaluating each sequence involves compiling, assembling, linking, execution and verification
  - simulation / execution on embedded processors is generally slower than general-purpose processors

- Reducing the search overhead
  - avoiding redundant executions of the application.
  - modifying the search to obtain comparable results in fewer generations.
Methods for Avoiding Redundant Executions

- Detect sequences that have already been attempted.
- Detect sequences of phases that have been successfully applied.
- Check if an instance of this function has already been generated.
- Check if an equivalent function has already been generated.
Reducing the Search Overhead

- Avoiding redundant executions.
- Obtaining similar results in fewer generations.
Overview of Avoiding Redundant Executions

- Genetic Algorithm
- Check Attempted Sequences
- Check Active Sequences
- Check for Equivalent Function
- Check for Identical Function
- Execute Application

Paths:
- candidate phases
- best sequence
- previous measure
- next sequence
- new measure
- apply phases
- calculate unmapped checksum
- calculate mapped checksum
- found
Finding Redundant Attempted Sequences

- Same optimization phase sequence may be reattempted
  - Crossover operation producing a previously attempted sequence
  - Mutation not occurring on any of the phases in the sequence
  - Mutation changing phases, but producing a previously attempted sequence
Finding Redundant Attempted Sequences (cont...)

**Before mutation**

| seq i : | d | a | e | d | c | f |
| seq j : | f | a | c | b | c | d |
| seq k : | f | e | c | b | b | d |

**After mutation**

| seq i : | d | a | e | d | c | f |
| seq j : | f | a | c | a | c | d |
| seq k : | f | a | c | b | b | d |
Finding Redundant Active Sequences

- An active optimization phase is one that is able to complete one or more transformations.
- Dormant phases do not affect the compilation.
- Compiler must indicate if phase was active.

![Diagram of sequences](image)
Detecting Identical Code

- Sometimes identical code for a function can be generated from different active sequences.

- Some phases are essentially independent – branch chaining and register allocation

- Sometimes more than one way to produce the same code.
Detecting Identical Code (cont…)

Example:

```plaintext
r[2] = 1;
⇒instruction selection
```

```plaintext
r[2] = 1;
⇒constant propagation
r[2] = 1;
```

```plaintext
⇒dead assignment elimination
```

Used CRC checksums to compare function instances.
Detecting Equivalent Code

- Code generated by different optimization sequences may be equivalent, but not identical.
- Some optimization phases consume registers.
- Different ordering of such phases may result in equivalent instructions, but different registers being used.
Detecting Equivalent Code (cont...)

```plaintext
sum = 0;
for (i = 0; i < 1000; i++)
    sum += a[i];
```

<table>
<thead>
<tr>
<th>Source Code</th>
<th>Register Allocation before Code Motion</th>
<th>Code Motion before Register Allocation</th>
<th>After Mapping Registers</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>r[10]=0;</code></td>
<td><code>r[11]=0;</code></td>
<td><code>r[32]=0;</code></td>
<td></td>
</tr>
<tr>
<td><code>r[12]=HI[a];</code></td>
<td><code>r[10]=HI[a];</code></td>
<td><code>r[33]=HI[a];</code></td>
<td></td>
</tr>
<tr>
<td><code>r[1]=r[12];</code></td>
<td><code>r[1]=r[10];</code></td>
<td><code>r[34]=r[33];</code></td>
<td></td>
</tr>
<tr>
<td><code>r[9]=4000+r[12];</code></td>
<td><code>r[9]=4000+r[10];</code></td>
<td><code>r[35]=4000+r[33];</code></td>
<td></td>
</tr>
<tr>
<td>L3</td>
<td>L3</td>
<td>L3</td>
<td></td>
</tr>
<tr>
<td><code>r[1]=r[1]+4;</code></td>
<td><code>r[1]=r[1]+4;</code></td>
<td><code>r[34]=r[34]+4;</code></td>
<td></td>
</tr>
<tr>
<td>IC=r[1]?r[9];</td>
<td>IC=r[1]?r[9];</td>
<td>IC=r[34]?r[35];</td>
<td></td>
</tr>
<tr>
<td>PC=IC&lt;0,L3;</td>
<td>PC=IC&lt;0,L3;</td>
<td>PC=IC&lt;0,L3;</td>
<td></td>
</tr>
</tbody>
</table>
Number of Avoided Executions

- **bit count**
- **dijkstra**
- **fft**
- **jpeg**
- **sha**
- **stringsearch**
- **average**

Legend:
- **暗红色** Equivalent
- **紫色** Identical
- **黄色** Active
- **浅蓝色** Attempted

Number of Avoided Executions

0 200 400 600 800 1000 1200 1400 1600 1800 2000
Relative Total Search Time

- bit count: 3.32 hours to 0.42 hours
- dijkstra: 2.50 hours to 0.63 hours
- fft: 3.24 hours to 1.75 hours
- jpeg: 20.45 hours to 9.29 hours
- sha: 1.73 hours to 0.35 hours
- stringsearch: 2.16 hours to 1.15 hours
- average: Not specified
Reducing the Search Overhead

- Avoiding redundant executions.
- Obtaining similar results in fewer generations.
Producing Similar Results in Fewer Generations

Can reduce search time by running the genetic algorithm for fewer generations.

Can obtain better results in the same number of generations.

We evaluate four methods for reducing the number of required generations to find the best sequence in the search.
Using the Batch Sequence

- Capture the active sequence of phases applied by the batch compiler.
- Place this sequence in the initial population.
- May allow the genetic algorithm to converge faster to the best sequence it can find.
Number of Generations When Using the Batch Sequence

- bit count
- dijkstra
- fft
- jpeg
- sha
- stringsearch
- average

Number of generations

Legend:
- Baseline
- Using the Batch Sequence
Prohibiting Specific Phases

Perform static analysis on the function.

- No loops, then no loop optimizations.
- No scalar variables, then no register allocation.
- Only one basic block, then no unreachable code elimination and no branch optimizations.
- Etc.

Such phases are prohibited from being attempted for the entire search for that function.
Number of Generations When Prohibiting Specific Phases

- bit count
- dijkstra
- fft
- jpeg
- sha
- stringsearch
- average

Bar chart showing the number of generations for different benchmarks. The x-axis represents the number of generations, ranging from 0 to 60. The y-axis lists the benchmarks. The chart compares the baseline with prohibiting specific phases.
Prohibiting Prior Dormant Phases

Some phases will be found to be dormant given a specific prefix of active phases.

If encounter the same prefix, then do not allow these prior dormant phases to be reattempted.

Keep a tree of active prefixes and store the dormant phases with each node in the tree.

Changed the genetic algorithm by forcing a prior dormant phase to mutate until finding a phase that has been active or not yet attempted with the prefix.
(cont…)

\(a\) and \(f\) are dormant phases given the active prefix of \(bac\) in the tree.
Number of Generations When Prohibiting Prior Dormant Phases

- bit count
- dijkstra
- fft
- jpeg
- sha
- stringsearch
- average

Bar chart showing the number of generations for different benchmarks when prohibiting prior dormant phases compared to the baseline.
Prohibiting Un-enabled Phases

Most optimization phases when performed cannot be applied again until enabled.
– ex: Register allocation will not be enabled by most branch optimizations

\[ \text{c enables a} \]
\[ \text{b and d do not enable a} \]
Prohibiting Unenabled Phases (cont.)

Assume \( b \) can be enabled by \( a \), but cannot be enabled by \( c \). Given the prefix \( bac \), then \( b \) cannot be active at this point.
Number of Generations When Prohibiting Unenabled Phases

- bit count
- dijkstra
- fft
- jpeg
- sha
- stringsearch
- average

Baseline
Prohibiting Un-enabled Phases

number of generations

Number of Generations When Applying All Techniques

- bit count
- dijkstra
- fft
- jpeg
- sha
- stringsearch
- average

number of generations
Number of Avoided Executions When Reducing the Number of Generations

- Bit count
- Dijkstra
- FFT
- JPEG
- SHA
- Stringsearch
- Average
Relative Search Time before Finding the Best Sequence

- **bit count**: 1.73 min to 0.54 min
- **dijkstra**: 19.26 min to 12.00 min
- **fft**: 0.50 min to 0.13 min
- **jpeg**: 190.05 min to 163.82 min
- **sha**: 9.13 min to 5.26 min
- **stringsearch**: 12.29 min to 6.99 min
- **average**:

The chart above shows the relative search time before finding the best sequence for various tasks, with the average time ranging from 0.54 min to 163.82 min.
Related Work

Superoptimizers
- instruction selection: Massalin
- branch elimination: Granlund, Kenner

Iterative compilation techniques using performance feedback information.
- loop unrolling, software pipelining, blocking

Using genetic algorithms to improve compiler optimizations
- Parallelizing loop nests: Nisbet
- Improving compiler heuristics: Stephenson et al.
- Optimization sequences: Cooper et al.
Future Work

- Detecting likely active phases given active phases that precede it.
- Varying the characteristics of the search.
- Parallelize the genetic algorithm.
Conclusions

Avoiding executions:

– Important for genetic algorithm to know if attempted phases were active or dormant to avoid redundant active sequences.
– Same code is often generated by different active sequences.

Reducing the number of generations required to find the best sequence in the search:

– Inserting the batch compilation active sequence is simple and effective.
– Can use static analysis and empirical data to often detect when phases cannot be active.