Performance Analysis of Embedded Software Using Implicit Path Enumeration

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Abstract — Embedded computer systems are characterized by the presence of a processor running application specific software. A large number of these systems must satisfy real-time constraints. This paper examines the problem of determining the bound on the running time of a given program on a given processor. An important aspect of this problem is determining the extreme case program paths. The state of the art solution here relies on an *explicit* enumeration of program paths. This runs out of steam rather quickly since the number of feasible program paths is typically exponential in the size of the program. We present a solution for this problem, which considers all paths *implicitly* by using integer linear programming. This solution is implemented in the program `cinderella` [1] which currently targets a popular embedded processor — the Intel i960. The preliminary results of using this tool are presented here.

I INTRODUCTION

A Motivation

Embedded computer systems are characterized by the presence of a processor running application specific dedicated software. Recent years have seen a large growth of such systems. This paper examines the problem of determining the extreme (best and worst) case bounds on the running time of a given program on a given processor. It has several applications in the design of embedded systems. In hard-real time systems the response time of the system must be strictly bounded to ensure that it meets its deadlines. These bounds are also required by schedulers in real-time operating systems. Finally, the selection of the partition between hardware and software, as well as the selection of the hardware components is strongly driven by the timing analysis of software.

B Problem Statement

A more precise statement of the problem addressed in this paper is as follows. We need to bound (lower and upper) the running time of a given program on a given processor assuming uninterrupted execution. The term "program" here refers to any sequence of code, and does not have to include a logical beginning and an end. The term "processor" here includes the complete processor and the memory system.

The running time of a program may vary according to different input data and initial machine state. Suppose that, of all the possible running times, T_{min} and T_{max} are the minimum and maximum of these times respectively. We define the *actual bound* of the program as the time interval $[T_{min}, T_{max}]$. Our objective is to find out a correct estimate of this without introducing undue pessimism. Thus, the estimated time interval $[t_{min}, t_{max}]$, defined as the *estimated bound*, must enclose the actual bound. This is illustrated in Fig. 1.

There are two components to the prediction of extreme case performance:

1. **program path analysis**, which determines what sequence of instructions will execute in the extreme case, and
2. **micro-architectural modeling**, which models the host processor system and computes how much time it will take for the system to execute that sequence.

Both these aspects need to be studied well in order to provide a solution to this problem. In our research we have attempted to isolate these aspects as far as possible in an attempt to clearly understand each problem. The focus of this paper is on program path analysis.

II PREVIOUS WORK

A static analysis of the code is needed to see what the possible extreme case paths through the code are. It is well accepted that this problem is undecidable in general and equivalent to the halting problem. Kligerman and Stoyenko [1] as well as Puschner and Koza [2] have suggested restrictions on programs that make this problem decidable. These are: absence

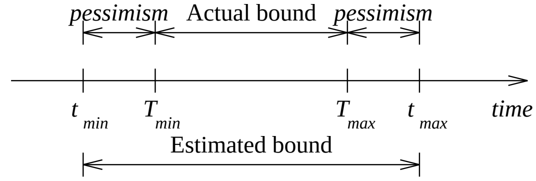

Fig. 1: Estimated bound $[t_{min}, t_{max}]$ and Actual bound $[T_{min}, T_{max}]$

[1] In recognition of her hard real-time constraint — she had to be back home at the stroke of midnight!

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of dynamic data structures, such as pointers and dynamic arrays; the absence of recursion; and bounded loops. These restrictions may be imposed either through specific language constructs, or programmer annotations on conventional programs. While specific language constructs, such as those provided in Real-Time Euclid [1], are useful in as much as they provide checks for the programs, they come with the usual high costs associated with a new programming language. Mok and his co-workers [3], Puschner and Koza [2], and Park and Shaw [4], adopt the latter approach. They all use annotations to existing programs to fix the bounds on loops. We believe that this approach is more practical, since it involves only minimal additional programming tools.

The timing analysis can be done at either the programming language level, or the assembly language level. Mok and his co-workers [3] use the high-level program description to provide functional information about the program through annotations which are then passed on to the assembly language program. We believe that this is the correct approach, the high-level language program is the right place to provide useful annotations, since that is what the programmer directly sees. However, the final analysis must be performed on the assembly language program so as to capture all the effects of the compiler optimizations and the micro-architectural implementation.

The functionality of the program determines the actual paths taken during its execution. Any information regarding this helps in deciding which program paths are feasible and which are not. While some of this information can be automatically inferred from the program, it is widely felt that this is a difficult task in general. In contrast, it is relatively easier for the programmer to provide such information since he/she is familiar with what the program is supposed to do [2]. Initial efforts [2, 3] to include this information were restricted to providing annotations about loop bounds and the maximum execution counts of a given statement within a given scope. This information, albeit useful, is very limited. It does not capture any information about the functional interactions between different parts of the program. Subsequent work by Park and Shaw [4] in this area attempts to overcome this limitation. They recognize that the set of statically feasible program paths and other path information can be expressed by regular expressions. The intersection of these regular expressions represents all the feasible paths, which can then be examined *explicitly* to determine the best and the worst case paths. Although the regular expression is powerful in describing all possible paths, it has several drawbacks. First, as the authors admit, these are not amenable for specification by programmers. The IDL language interface provided to the programmer is an exercise in compromise, giving up full generality for ease of use and analysis. Even so, the complexity of intersecting regular expressions and the need to examine explicitly a potentially exponential number of paths is still very prohibitive. In many cases, this results in the use of approximate solutions.

The main contribution of this paper is to provide a method that *does not* explicitly enumerate program paths, but rather *implicitly* considers them in its solution. This is accomplished by converting the problem of determining the bounds to one of solving a set of integer linear programming (ILP) problems. While each ILP problem can in the worst case take exponential time, in practice exponential blowup never occurred in our experiments. In fact, we observed that in practice, the actual computation done by the ILP solver is solving a single linear program. The reasons for this will be briefly examined in Section III, and practical data supporting this will be presented in Section VI.

[2] There is an analog of this in the domain of digital circuits. There, designer annotations were commonly used to mark paths in the digital circuit that were never exercised [5]. These paths were then eliminated from consideration in the timing analysis of the circuit.

III ILP Formulation

A Objective Function

Our objective is to determine the extreme case running times and not necessarily actually identify the extreme case paths. This observation led to the following formulation of the problem. For the rest of this section, the focus will be the worst case timing, the best case can be obtained analogously. Let x_i be the number of times the basic block B_i is executed when the program takes the maximum time to complete. A basic block of code is a maximal sequence of instructions for which the only entry point is the first instruction and the only exit point is the last instruction. Let c_i be the running time (or cost) of this basic block in the worst case. For now let us assume that c_i is constant over all possible times this basic block is executed. This issue will be examined in more detail in Section IV. Thus, if there are N basic blocks in the program, the worst case timing for the program is given by the maximum value of the expression:

$$\sum_{i=1}^{N} c_i x_i. \tag{1}$$

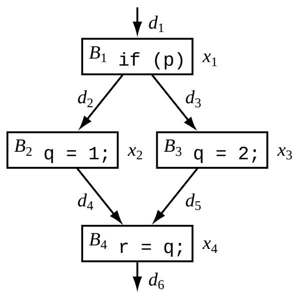
Clearly, x_i's cannot be any value. They are constrained by the program structure and the program functionality, which deals with what the program is computing and depends on the data variables. What we need to do is to maximize (1) while taking into account the restrictions imposed by the program structure and functionality. Since (1) is a linear expression, if we can state these restrictions in the form of linear constraints, it will enable us to use ILP to determine the maximum value of the expression. In the following subsections we will demonstrate how this can be done.

B Program Structural Constraints

The structural constraints are extracted automatically from the program's control flow graph (CFG) [6]. This is illustrated in Fig. 2, which contains an `if-then-else` statement and its CFG. In the CFG, we label the edges and the basic blocks by variables d_i's and x_i's respectively. These variables represent the number of times that the control is passing through those edges and basic blocks when the code is executed. The constraints can be deduced from the CFG as follows: At each node, the execution count of the basic block is equal to both the sum of the control flow going into it, and the sum of the control flow going out from it. Thus, from the graph, we have the following constraints:

$$x_1 = d_1 = d_2 + d_3 \tag{2}$$

```
if (p)
  q = 1;
else
  q = 2;
r = q;
```



(i) Code (ii) CFG

Fig. 2: An example of the `if-then-else` statement and its CFG.

$$
\begin{aligned}
x_2 &= d_2 = d_4 && (3)\\
x_3 &= d_3 = d_5 && (4)\\
x_4 &= d_4 + d_5 = d_6 && (5)
\end{aligned}
$$

Fig. 3 shows a `while`-loop statement and its CFG. The constraints are:

$$
\begin{aligned}
x_1 &= d_1 = d_2 && (6)\\
x_2 &= d_2 + d_4 = d_3 + d_5 && (7)\\
x_3 &= d_3 = d_4 && (8)\\
x_4 &= d_5 = d_6 && (9)
\end{aligned}
$$

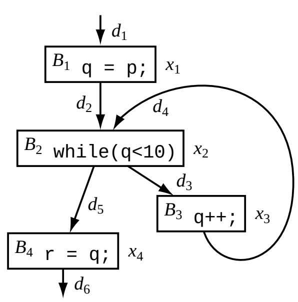
Note that the above constraints do not contain any loop count information. This is because the loop count information depends on the values of the variables, which are not tracked in the CFG. However, the loops can be detected and marked. After all the structural constraints have been constructed, the user will be asked to provide the loop bound information as part of specifying the program functionality constraints (see Section C).

The function calls are represented by using f-edges in the CFG as shown in Fig. 4. An f-variable is similar to a d-variable, except that its edge contains a pointer pointing to the CFG of the function being called. The construction of structural constraints in the caller function remains the same. They are:

$$
\begin{aligned}
x_1 &= d_1 = f_1 && (10)\\
x_2 &= f_1 = f_2 && (11)
\end{aligned}
$$

The number of times that the function is executed can be tracked by knowing the f-edges pointing to it. In our example,

```
/* p >= 0 */
q = p;
while(q<10)
  q++;
r = q;
```

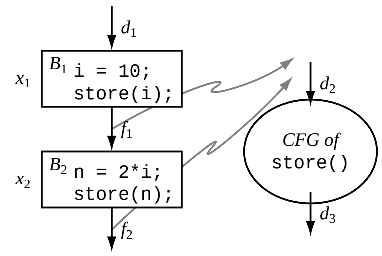


(i) Code (ii) CFG

Fig. 3: An example of the `while`-loop statement and its CFG.

```
i = 10;
store(i);
n = 2*i;
store(n);

void store(int i)
{
  ...
}
```



(i) Code (ii) CFG

Fig. 4: An example showing how function calls are represented.

this information is represented by:

$$d_2 = f_1 + f_2 \quad (12)$$

where d_2 is the first edge of the function `store()`'s CFG. For the main function, which has d_1 as its first edge in the CFG, the following constraint is constructed.

$$d_1 = 1 \quad (13)$$

C Program Functionality Constraints

These constraints are provided by the user to denote loop bounds and other path information that depend on the functionality of the program. We illustrate the use of these constraints to capture conditions on feasible program paths with the example (Fig. 5) taken from Park's thesis [4]. The function `check_data()` checks the values of the `data[]` array. If any of them is less than zero, the function will stop checking and return 0, otherwise it will return 1.

The while-loop in the function will be executed between 1 and `DATASIZE` times. Suppose that `DATASIZE` is previously defined as a constant value 10, then the following constraints are used to specify this loop bound information.

$$
\begin{aligned}
1x_1 &\leq x_2 && (14)\\
x_2 &\leq 10x_1 && (15)
\end{aligned}
$$

Here, x_1 is the count for the basic block just before entering the loop and x_2 is the count for the first basic block inside the loop.

```
        check_data()
        { int i, morecheck, wrongone;

x1        morecheck = 1; i = 0; wrongone = -1;
          while (morecheck) {
x2          if (data[i] < 0) {
x3            wrongone = i; morecheck = 0;
            }
            else
x4            if (++i >= DATASIZE)
x5              morecheck = 0;
x6        }

x7        if (wrongone >= 0)
x8          return 0;
          else
x9          return 1;
        }
```

Fig. 5: `check_data` example from Park's thesis. The x_i variables denote the execution counts of their corresponding basic blocks.

Since all the loops are marked, these two variables can be determined automatically. All the user has to provide are the values 1 and 10.

The minimum user information required to perform timing analysis is the loop bound information. After that, the user can provide addition information so as to tighten the estimated bound. For example, we see that inside the loop, line 6 and line 10 are mutually exclusive and either of them is executed at most once. This information can be represented by:

$$(x_3 = 0 \;\&\; x_5 = 1) \mid (x_3 = 1 \;\&\; x_5 = 0) \tag{16}$$

The symbols '&' and '|' represent conjunction and disjunction respectively. Note that this constraint is not a linear constraint by itself, but a disjunction of linear constraint sets. This can be viewed as a set of constraint sets, where at least one constraint set member must be satisfied.

As an another example, line 6 and line 13 are always executed together for the same number of times. This can be represented by:

$$x_3 = x_8 \tag{17}$$

The path information is not limited to within a function. The user may also specify the path relationship between the caller and the callee function. This is illustrated in the example shown in Fig. 6. We see that the function `clear_data()` will only be executed if the return value from the function `check_data()` is 0. This information can be represented by the constraint:

$$x_{12} = x_8 . f_1 \tag{18}$$

Here, the dot symbol '.' in $x_8 . f_1$ means that the count of basic block B_8 in function `check_data()` when called at location f_1. If the function `check_data()` is called from other places, the value of x_8 will not affect that of x_{12}. For purpose of analysis, a separate set of x_i variables is used for this instance of the call to function `check_data()`.

Since the functionality constraints are serving the same purpose as constructs in the IDL language provided by Park in his work [4], it is instructive to compare their relative expressive powers. We have been able to demonstrate that every construct in IDL can be translated to a disjunctive form constraint. In addition, we can provide disjunctive constraints for practically useful annotations that are beyond the capabilities of IDL. A complete proof of this claim is beyond the scope of this paper.

```
             check_data()
             { ...
x7             if (wrongone >= 0)
x8               return 0;
               else
x9               return 1;
             }

             task()
             { ...
x10, f1        status = check_data();
x11            if (!status)
x12, f2          clear_data();
               ...
             }
```

Fig. 6: An example showing how the path relationship between the caller and the callee function can be specified.

D Solving the Constraints

The program structural constraint set is a set of constraints that are conjunctive, i.e., they must all be satisfied simultaneously. Because of the disjunction '|' and conjunction '&' operators, the program functionality constraints may, in general, be a disjunction of conjunctive constraint sets. Giving us a set of constraint sets, at least one of which is satisfied for any assignment to the x_i's. For example, by intersecting all the functionality constraints ((14) through (17)), we will obtain two functionality constraint sets:

First set	Second set
$x_1 - x_2 \leq 0$	$x_1 - x_2 \leq 0$
$10x_1 - x_2 \geq 0$	$10x_1 - x_2 \geq 0$
$x_3 = 0$	$x_3 = 1$
$x_3 - x_8 = 0$	$x_3 - x_8 = 0$
$x_5 = 1$	$x_5 = 0$

To estimate the running time, each set of the functionality constraint sets is combined (the conjunction taken) with the set of structural constraints. This combined constraint set is passed to the ILP solver with (1) to be maximized. The ILP solver returns the maximum value of the expression, as well as basic block counts (x_i values) that result in this maximum value. The above procedure is repeated for every set of functionality constraint sets. The maximum over all these running times is the maximum running time of the program. Note that a single value of the basic block counts for the worst case is provided in the solution even if there are a large number of solutions all of which result in the same worst case timing. The ILP solver in effect has implicitly considered all paths (different assignments to the x_i variables) in determining the worst case.

The total time required to solve the problem depends on the number of functionality constraint sets, and the time required to solve each constraint set. The size of the constraint sets is doubled every time a functionality constraint with disjunction operator '|' is added. While no theoretical bounds on this can be derived, our observations have been that in practice this is not a problem. We found the size to be small at the beginning, and as more constraints are added, some of the constraint sets will become a null set (e.g. $x_i \geq 1$ intersected with $x_i = 0$). These trivial null sets, if detected, will be pruned before being passed to ILP solver. The second issue is the complexity of solving each ILP problem, which is, in general, an *NP*-complete problem. We were able to demonstrate that if we restrict our functionality constraints to those that correspond to the constructs in the IDL language, then the ILP problem is equivalent to a network flow problem, which can be solved in polynomial time. However, the full generality of the functionality constraints can result in it being a general ILP problem. In practice, this was never experienced, i.e., in the branch and bound solution to the ILP, the first call to the linear program package resulted in an integer valued solution. More specific data will be provided in Section VI.

IV MICRO-ARCHITECTURAL MODELING

Currently we are using a simple hardware model to determine the bound of the running time (cost) of a basic block. For each assembly instruction in the basic block, we analyze its adjacent instructions within the basic block, and determine the bound on its effective execution time from the hardware manual. The bound of the complete basic block is obtained by summing up all the bounds of the instructions. This model can handle pipelining reasonable well. However, it is very simplistic in its approach to modeling cache memory. Since the costs must be constants, for best case running time, we assume the execution always has cache-hits, whereas, for worst case running time, we assume that the execution will always result in cache-misses. Although this still gives a valid estimated bound on the program's execution time, it is clearly a conservative approximation and needs to be tightened. In particular, it may happen that the first iteration of a loop results in cache misses, while the subsequent iterations will result in cache-hits. Assuming that all iterations result in all cache misses can be very pessimistic. This pessimism can easily be avoided in the path analysis stage by considering the first iteration of the loop as a separate basic block, distinct from the other iterations, with its own x_i and c_i variables. We are currently working on the modeling of cache memory. Several other researchers are also looking into this problem [7].

V IMPLEMENTATION

We have developed a tool called `cinderella` that incorporates the ideas presented in this paper for timing analysis. It contains approximately 8,000 lines of C++ code. Currently, `cinderella` is implemented to estimate the running time of programs running on an Intel i960KB processor. The processor is a 32 bit RISC processor that is being used in many embedded systems (e.g. in laser printers). It contains a 4-stage pipelined execution unit, a floating point unit and a 512-byte direct-mapped instruction cache [8].

`Cinderella` first reads the executable code for the program. It then constructs the CFG and derives the program structural constraints. Next, it reads the source files and outputs the annotated source files, where all the x_i and f_i variables are labelled alongside with the source code (Fig. 5). Then, for all loops in the program it asks the user to provide the loop bounds. This is all the information that is mandatory to provide the timing bounds, and an initial estimate of these bounds can be obtained at this point. To tighten the estimated bound, the user can provide additional functionality constraints and re-estimate the bounds again. After each estimation, `cinderella` outputs the estimated bound (in units of clock cycles), the basic blocks' costs and their counts.

VI EXPERIMENTAL RESULTS

Our solution is not guaranteed to give the exact bounds, and in general some pessimism will be introduced in the estimation. There are two sources for the pessimism in (1): the pessimism in c_i's and the pessimism in x_i's. The former pessimism results from the inaccuracies of the micro-architectural modeling. It can be reduced by improving the modeling. The latter is due to insufficient path information, so that some infeasible paths are considered to be feasible. This can hopefully be reduced by providing more functionality constraints.

Since our current work focuses on the path analysis problem, we would like to evaluate the efficacy of our methodology in determining the worst and best case paths. Experiment 1 described below is directed towards evaluating the pessimism in path analysis. In addition to this, we also conducted Experiment 2, with the goal of measuring the inadequacies in our current micro-architectural modeling.

A Experiment 1: Evaluating the Path Analysis Accuracy

Since there are no established benchmarks for this purpose, we collected a set of example programs from a variety of sources for this task. Some of them are from academic sources: from Park's thesis [4] on timing analysis of software and also from Gupta's thesis [9] on the hardware-software co-design of embedded systems. Others are from standard DSP applications, as well as software benchmarks used for evaluating optimizing compilers. These routines, their sizes and the number of constraint sets being passed to the ILP solver are shown in Table I. Of the eight constraint sets of function `dhry`, five of them are detected as null sets and eliminated. For each routine, we obtain the estimated bound by using `cinderella` and calculate the *calculated bound*, which is obtained by the following steps:

1. Insert a counter into each basic block of the routine.
2. Identify the initial data set that corresponds to the longest (shortest) running time of the routine.
3. Run the routine with that data set and record the values of all the counters.
4. Multiply each counter value with the slowest (fastest) running time for that basic block as provided by `cinderella`.
5. Add up all these products. This is the upper (lower) bound of the calculated bound.

Note that in order to find the actual upper (lower) bound on the execution time, we would have to run the routine for all possible inputs. This is clearly not feasible. Thus, we have replaced this step by actually trying to identify the best (worst) case data set by a careful study of the program. Clearly if we could rely on this identification of the best and the worst case, we do not need to do the analysis at all. However, as we have no other mechanism to evaluate the result, we have to use this method. We do know however, that if the analysis result agrees with our selection of the data set, then it will be the worst case data set and also our analysis is completely accurate. As the results of Experiment 1 show (Table II), the analysis provides results that are either in agreement with the selection of the data set, or very close to it. The pessimism in the evaluation measures the relative difference between the calculated bound $[C_l, C_u]$ and the estimated bound $[E_l, E_u]$. It is defined as $[\frac{C_l - E_l}{C_l}, \frac{E_u - C_u}{C_u}]$.

Function	Description	Lines	Sets
`check_data`	Example from Park's thesis	17	2
`fft`	Fast Fourier Transform	56	1
`piksrt`	Insertion Sort	15	1
`des`	Data Encryption Standard	185	2
`line`	Line drawing routine in Gupta's thesis	143	1
`circle`	Circle drawing routine in Gupta's thesis	88	1
`jpeg_fdct_islow`	JPEG forward discrete cosine transform	150	1
`jpeg_idct_islow`	JPEG inverse discrete cosine transform	246	1
`recon`	MPEG2 decoder reconstruction routine	137	1
`fullsearch`	MPEG2 encoder frame search routine	204	1
`whetstone`	Whetstone benchmark	245	2
`dhry`	Dhrystone benchmark	480	$8 \Rightarrow 3$
`matgen`	Matrix routine in Linpack benchmark	50	1

TABLE I: SET OF BENCHMARK EXAMPLES

Function	Estimated Bound	Calculated Bound	Pessimism
check_data	[32, 1,039]	[32, 1,039]	[0.00, 0.00]
fft	[0.97e6, 3.35e6]	[0.98e6, 3.31e6]	[0.01, 0.01]
piksrt	[146, 4,333]	[146, 4,333]	[0.00, 0.00]
des	[42,302, 604,169]	[43,254, 592,559]	[0.02, 0.02]
line	[336, 8,485]	[336, 8,485]	[0.00, 0.00]
circle	[502, 16,652]	[502, 16,301]	[0.00, 0.02]
jpeg_fdct_islow	[4,583, 16,291]	[4,583, 16,291]	[0.00, 0.00]
jpeg_idct_islow	[1,541, 20,665]	[1,541, 20,665]	[0.00, 0.00]
recon	[1,824, 9,319]	[1,824, 9,319]	[0.00, 0.00]
fullsearch	[43,082, 244,305]	[43,085, 244,025]	[0.00, 0.00]
whetstone	[4.54e6, 13.7e6]	[4.54e6, 13.7e6]	[0.00, 0.00]
dhry	[0.22e6, 1.26e6]	[0.22e6, 1.26e6]	[0.00, 0.00]
matgen	[5,507, 13,933]	[5,507, 13,933]	[0.00, 0.00]

TABLE II: PESSIMISM IN PATH ANALYSIS.

From these results, we see that when given enough information, the path analysis can be very accurate. The CPU times taken for each ILP problem were insignificant, less than 2 seconds on an SGI Indigo Workstation. This is largely due to the fact that the branch-and-bound ILP solver finds that the solution of the very first linear program call it makes is integer valued.

B Experiment 2: Comparison with Actual Running Times

In this experiment, we measured the actual running time of the program and compared it with the estimated bound. Each program is compiled and then run on an Intel QT960 board [10], which is a development board containing a 20MHz i960KB processor, memory and some other peripherals. To measure the worst case running time, we initialize the routine with its worst case data set and then run it in a loop several hundred times and measure the elapsed time. The cache memory is flushed before each function call. Since this value includes the time to do the loop iterations and cache flushing, we run an empty loop and measure its execution time again. The difference between these two values is the actual running time of the routine. The best case running time is obtained analogously, but without the cache flush.

Table III shows the results of this experiment. The estimated bound is the same as in Experiment 1. The measured values described above are shown in the measured bound column. The pessimism is defined as $[\frac{M_l - E_l}{M_l}, \frac{E_u - M_u}{M_u}]$ where $[M_l, M_u]$ denotes the measured bound.

We observe that while the estimated bound does enclose the measured bound, the pessimism in the estimation is rather high. This is mainly due to the fact that a simple hardware model is used. In particular, the pessimism is bigger when there are many small basic blocks in the function. This is because all the cost analysis is currently being done within the basic block.

Function	Estimated Bound	Measured Bound	Pessimism
check_data	[32, 1,039]	[38, 441]	[0.16, 1.36]
fft	[0.97e6, 3.35e6]	[1.93e6, 2.05e6]	[0.50, 0.63]
piksrt	[146, 4,333]	[338, 1,786]	[0.57, 1.43]
des	[42,302, 604,169]	[109,329, 242,295]	[0.61, 1.49]
line	[336, 8,485]	[963, 4,845]	[0.65, 0.75]
circle	[502, 16,652]	[641, 14,506]	[0.22, 0.15]
jpeg_fdct_islow	[4,583, 16,291]	[7,809, 10,062]	[0.41, 0.62]
jpeg_idct_islow	[1,541, 20,665]	[2,913, 13,591]	[0.47, 0.52]
recon	[1,824, 9,319]	[4,566, 4,614]	[0.60, 1.02]
fullsearch	[43,082, 244,305]	[62,463, 62,468]	[0.31, 2.91]
whetstone	[4.54e6, 13.71e6]	[6.83e6, 6.83e6]	[0.34, 1.01]
dhry	[218,013, 1,264,430]	[551,460, 551,840]	[0.60, 1.29]
matgen	[5,507, 13,933]	[9,260, 9,280]	[0.41, 0.50]

TABLE III: DISCREPANCY BETWEEN THE ESTIMATED BOUND AND THE MEASURED BOUND.

For blocks with only a few assembly instructions, the cache and pipeline behavior is not being modeled very accurately because they depend a lot on the surrounding instructions. Consequently, the costs of these blocks are loose and these contribute to the discrepancy between the estimated and the measured bounds. A more sophisticated micro-architectural modeling will certainly improve the accuracy of the estimated bound.

VII CONCLUSIONS AND FUTURE WORK

In this paper, we have presented an efficient method to estimate the bounds of the running time of a program on a given processor. The method uses integer linear programming techniques to perform the path analysis without explicit path enumeration. It can accept a wide range of information on the functionality of the program in the form of sets of linear constraints. A tool called `cinderella` has been developed to perform this timing analysis. Experimental results on a set of examples show the efficacy of this approach.

The future work includes improving the hardware model to take into account the effects of cache memory and other features of modern processors that tend to make the timing relatively non-deterministic. We would also like to explore the possibility of using symbolic analysis techniques to automatically derive some of the functionality constraints. Finally, we are working on porting `cinderella` to handle programs running on other hardware platforms. In collaboration with AT&T, we have completed a port for the AT&T DSP3210 processor. This is intended for use in the VCOS operating system to bound the running times of processes for use in scheduling.

REFERENCES

[1] Eugene Kligerman and Alexander D. Stoyenko, "Real-time Euclid: A language for reliable real-time systems", *IEEE Transactions on Software Engineering*, vol. SE-12, no. 9, pp. 941–949, September 1986.

[2] P. Puschner and Ch. Koza, "Calculating the maximum execution time of real-time programs", *The Journal of Real-Time Systems*, vol. 1, no. 2, pp. 160–176, September 1989.

[3] Aloysius K. Mok, Prasanna Amerasinghe, Moyer Chen, and Kamtron Tantisirivat, "Evaluating tight execution time bounds of programs by annotations", in *Proceedings of the 6th IEEE Workshop on Real-Time Operating Systems and Software*, May 1989, pp. 74–80.

[4] Chang Yun Park, *Predicting Deterministic Execution Times of Real-Time Programs*, PhD thesis, University of Washington, Seattle 98195, August 1992.

[5] R. B. Hitchcock, "Timing Verification and the Timing Analysis Program", in *Proceedings of the* 19^{th} *Design Automation Conference*, June 1982, pp. 594–604.

[6] Alfred V. Aho, Ravi Sethi, and Jeffery D. Ullman, *Compilers Principles, Techniques, and Tools*, Addison-Wesley, 1986, ISBN 0-201-10194-7.

[7] Byung-Do Rhee, Sang Lyul Min, Sung-Soo Lim, Heonshik Shin, Chong Sang Kim, and Chang Yun Park, "Issues of advanced architectural features in the design of a timing tool", in *Proceedings of the 11th IEEE Workshop on Real-Time Operating Systems and Software*. May 1994, pp. 59–62, IEEE Computer Soc. Press, ISBN 0-8186-5710-3.

[8] Intel Corporation, *i960KA/KB Microprocessor Programmers's Reference Manual*, 1991, ISBN 1-55512-137-3.

[9] Rajesh Kumar Gupta, *Co-Synthesis of Hardware and Software for Digital Embedded Systems*, PhD thesis, Stanford University, December 1993.

[10] Intel Corporation, *QT960 User Manual*, 1990, Order Number 270875-001.