ABSTRACT

DHOOT, ANUBHAV V. Hybrid online/offline optimization of application binaries (Under the direction of Assistant Professor Dr. Frank Mueller).

Long-running parallel applications suffer from performance limitations particularly due to inefficiencies in accessing memory. Dynamic optimizations, i.e., optimizations performed at execution time, provide opportunities not available at compile or link time to improve performance and remove bottlenecks for the current execution. In particular, they enable one to apply transformations to tune the performance for a particular execution instance. This can potentially include effects of the environment as well as be able to optimize code from other sources like pre-compiled libraries and code from mixed-language sources. This thesis presents design and implementation of components of a dynamic optimizing system for long-running parallel applications that use dynamic binary rewriting. The system uses a hybrid online/offline model to collect a memory profile that guides the choice of functions to be optimized. We describe the design and implementation of a module that enables optimization of a desired function from the executable, i.e., without relying on the source code. We also present the module that enables hot swapping of code of an executing application. Dynamic binary rewriting is used to hot-swap the bottleneck function with an optimized function while the application is still executing. Binary manipulation is used in two ways - first to collect a memory profile through instrumentation to identify bottleneck functions and then to control hot-swapping of code using program transformation. We show experiments as a proof of concept for implementations of remaining components of the framework and for validation of existing modules.

Hybrid online/offline optimization of application binaries

by

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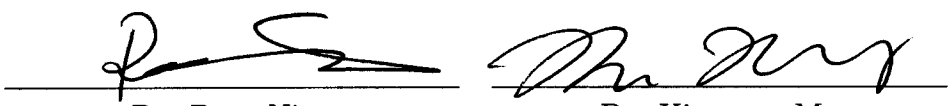

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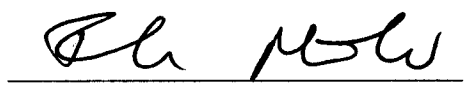

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Biography

Anubhav Dhoot was born on 4^{th} December 1980. He is from Bombay, India, and he received his Bachelor of Engineering in Computer Science from Vivekanand Education Society's Institute of Technology located in the same city in 2002. He started his graduate studies at the North Carolina State University in Fall 2002. With the defense of this thesis, he is receiving the Master of Science in Computer Science degree from NCSU in August 2004.

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Chapter 1

Introduction

1.1 Motivation

Optimizations are usually applied at compile-time, link-time or post-link time. While compile time and link-time optimizations help to optimize functions considerably, they still leave opportunities for further improvement. This is because these optimization techniques suffer from limitations, such as lack of access to profiling data for the deployed scenario. None of these techniques can leverage current execution environment conditions. Compile-time techniques depend on availability of source code. Even though these techniques have access to a lot more information that is lost after link time, they cannot cater to code for which they do not have access to the sources, examples, pre-compiled shared libraries and mixed-language code. It is also difficult for these techniques to optimize for all possible scenarios in which the executable will be deployed.

Optimizations applied post-link time, but just before execution, eg. optimizations in Just In Time (JIT) compilations [GAH+00],[KF01], have to suffer from time constraints for applying optimizations. This is because compilation time for applying optimizations would be exerted as part of the execution time, in particular, just before instructions from the application are executed.

Long-running application binaries, mainly parallel applications, suffer from various performance limitations, chiefly due to bottlenecks in accessing the memory hi-

erarchy. Dynamic optimizations, i.e., post-link time optimizations performed at run-time, can provide code of higher quality because we can leverage profiling information. Optimizing at run-time can allow us to capture memory references of the entire application including pre-compiled library routines and of mixed-language applications, which is crucial as numerous scientific production codes are mixed-language based. Dynamic optimizations can also cater to input dependencies, application modes and user behavior by using profile behavior that we collect from actual execution. However, use of input information as part of optimizations is beyond the scope of this thesis.

There exist feedback directed optimizations schemes that use feedback to guide the optimizations applied. But these use feedback from a training input or from previous executions that may exhibit a behavior different from the current deployed scenario.

Also, dynamic optimization can be performed at idle time between execution runs or in parallel to the executing application. Hence it does not suffer from time constraints in applying optimizations.

We are designing a dynamic optimization framework that uses binary manipulation techniques. We use binary manipulation techniques in two ways. First we use binary manipulation to collect execution profile, including memory hierarchy statistics, of the executing application, using instrumentation. The profile is used to identify the bottleneck function that is optimized. We then rewrite optimized code back into the executing application via dynamic binary rewriting. This enables the rest of the execution to benefit from the optimization, thus obviating the need to restart the application. Profiling time can be recouped easily for long-running applications, as the optimized code will be faster than the original code. Also, we can control the duration of the period when the application suffers from the overhead of profiling instrumentation.

1.2 Hybrid Mechanism

Dynamic optimizations are usually performed totally online or offline. In online schemes, a monitor program continually monitors the application and it analyzes the statistics it collects. The monitor may decide to optimize any function either by interrupting the application and optimizing the function or while the application continues but using the same shared hardware resources, such as the processor and cache. Both steps add a considerable overhead to the application execution that needs to be recouped from the benefits obtained from optimizations. Offline schemes typically collect profiles from either training runs or previous runs. When the application finishes an execution run, the optimizing module will apply optimizations and use the optimized code during the next execution. We use a hybrid mechanism described below that enables us to optimize code without requiring that the application be restarted.

We use a hybrid (online/offline) approach for our entire cycle of replacing existing functions with optimized functions. First, an online process is used to collect memory hierarchy statistics using instrumentation. We analyze these statistics offline while the application continues without instrumentation. After we have identified the bottleneck function and we have chosen to optimize it, we optimize the function, again offline. When going online, we rewrite back the new function to replace the old function and let the application continue. Optimizations do not contribute to the execution overhead and the time spent in optimizing the function is not constrained, as optimizations are performed offline.

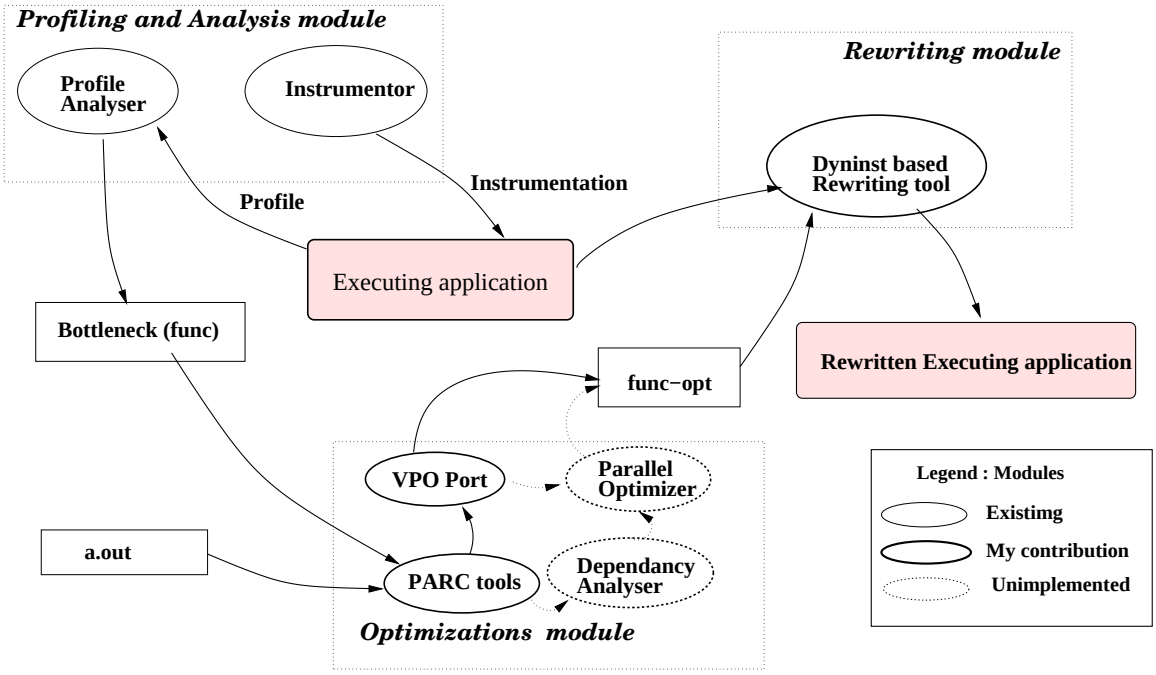

Figure 1.1: Current Implementation status

The current state of the implementation is shown in Figure 1.1. The preexisting profiling and analysis module was developed in our group before. This allows us to collect memory statistics from an executing application. Currently, we have designed and implemented two major modules. The first, termed optimizing module, contains components (VPO and PARC tools) that enable us to apply scalar optimizations to a function from an executable format. The other, termed as rewriting module, enables us to rewrite an optimized function into an executing application. The missing link is a component in the optimizing module to enable us to apply parallel optimizations. This requires another component that derives loop and data-dependence information from the executable. Once the optimizing module is complete, we can automate various transformations to optimize resource-intensive parallel applications.

1.3 Outline

This thesis is organized as follows. I will describe the Overall architecture in section 2. I will then describe issues about the design and implementation of various modules. First, I describe the model of VPCC/VPO [BD94, BD88], the optimizing compiler on which the optimizations module is built. I describe issues we encountered in porting the compiler to the POWER architecture, i.e., the architecture on which we are implementing our framework. I will then describe the design and issues with the implementation of the PARC (Power Assembly to RTL Converter) tools that convert POWER assembly to intermediate format that can be fed into the compiler VPO. I also describe various related tools and the tool chain that leads to an optimized function from the executable. I will lastly describe the dynamic binary rewriting tool that enables us to hot-swap functions without requiring us to restart the application.

1.4 My contribution

I was involved with another student, Jaydeep Marathe, in porting the VPCC/VPO C compiler to the POWER architecture. VPCC forms the front-end of the compiler and VPO is the back-end. I was responsible for implementing the floating-point com-

ponents of the compiler. Along with implementing the code translation component, we had to resolve various issues dealing with binary compatibility with code generated by other compilers like *xlc*. Later I was solely responsible for the module to derive a function from the executable to an intermediate form that can be fed into VPO. The heart of this module was the PARC tool I wrote. PARC is a *lex-yacc* based parser of POWER assembly whose output is in the format accepted by the version of VPO we ported. While implementing it, I had to extend VPCC/VPO to support more instructions. Initially the compiler supported only a subset of the instruction set that was enough for it compile arbitrary source code. But as disassembly from an executable could potentially contain any instruction, I had to add instructions in VPCC/VPO and then add support in the PARC tool. I also wrote a tool named PrePARC that would preprocess disassembly output, performing functions like adding labels and correcting the output when the disassembly utility incorrectly disassembles data as text. Finally, I had to extend a basic function hot-swapping program via dynamic binary rewriting using the Dyninst API [BH00] to allow us to hot-swap a function in an executing application, by attaching to it and applying instrumentation, while maintaining consistency of program semantics.

Chapter 2

Description of the Overall Architecture

There are 3 major modules in our architecture - the profiling and analysis module, the optimizing module and the rewriting module.

The overall architecture is shown in Figure 2.1.

The entire optimization cycle being described can be performed periodically during different phases of the application execution. Each cycle consists of the following steps. The profiling and analysis module first determines the bottleneck function of the current execution phase of the application. In order to identify the bottleneck function, we examine the current execution profile that will provide insights on the memory behavior. To build the execution profile for the current phase of execution, we use binary instrumentation to modify the application to extract a memory access trace. Instrumentation is added for a fixed time interval and is then removed.

The name of the bottleneck function (say *func*) is provided to the optimization module. The optimization module uses the executable (*a.out*) and the name of the function (*func*) to extract the existing function and optimize it to remove performance bottlenecks. The optimized function (*func optimized*) is generated as a shared library, which is provided to the rewriting module. The rewriting module modifies the executing application so that all calls to the original function (*func*) use the newly optimized version of the function (*func optimized*).

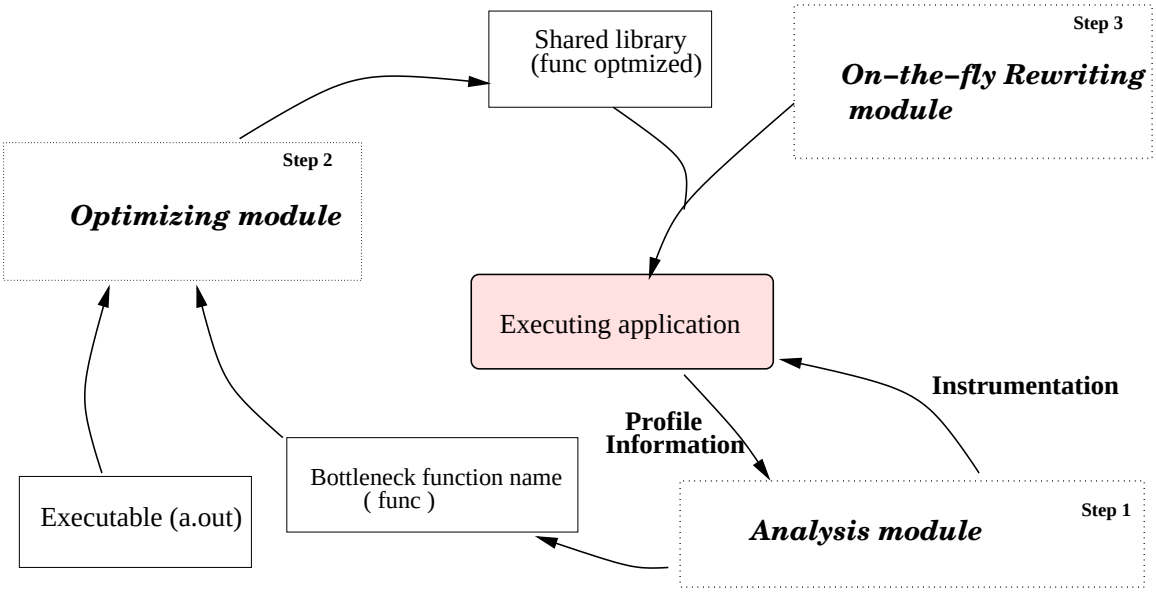

Figure 2.1: Overall Architecture

Next, the profiling and analysis module is briefly described.

We add profile-generating instrumentation to the executing executable via binary rewriting in order for it to generate memory statistics. We interrupt the application to rewrite the executable in order to add instrumentation. We then let the application continue. After the statistics are generated, the application is interrupted to remove the profiling instrumentation. The application is then allowed to continue again without any instrumentation. The profiling step is online while the analysis can be performed offline, i.e., in parallel on disjoint hardware resources while the application continues. The analysis step, thus, does not add any execution overhead.

We leverage previous work of our group via the METRIC framework described in detail in [MM02] and [MM03]. METRIC determines memory inefficiencies by examining traces. It extracts partial traces via binary rewriting. It uses online compression of memory traces and offline cache simulations that enables it to pinpoint memory performance bottlenecks without much overhead to the executing application.

The analysis module determines the name of the bottleneck function in the current execution phase of the application. This is input to the optimization module to apply optimizations to the function in order to remove the bottlenecks.

The optimizations module contains the following components as shown in Figure 2.2.

The PrePARC and PARC tools extract the bottleneck function (*func*) from the executable and convert it into an intermediate format. The function in intermediate format is provided to the optimizer based on VPO. PARC is a parser of POWER assembly, whose output is in the format accepted by VPO. The PrePARC tool preprocesses the disassembly of the linked executable, that is obtained from the disassembler. We use the *objdump* tool, part of *binutils* toolset for AIX, as the disassembler.

In brief VPCC/VPO is an optimizing compiler that translates source code to a machine-independent intermediate format. The intermediate format, termed as RTL (Register Transfer Lists) [Ben91], indicates assembly instructions as register transfer operations. VPCC/VPO performs optimizations repeatedly on the RTL format and ultimately converts the RTLs to assembly form. VPCC/VPO performs a set of scalar optimizations. An optimizer module, that is beyond the scope of this thesis, needs to be implemented. It will perform parallel optimizations, on loops and arrays. This would, in turn, require loop and data dependency information to be collected from the executable, another aspect of future work.

After all optimizations are applied, the optimized function code is generated in the form of a shared library. The rewriting module then modifies the executing application, adding the shared library and modifying the executable, to utilize the optimized version of the function from that point on. The optimizing module executes offline, on disjoint hardware resources, e.g., a separate processing node, and in parallel while the application is still executing. This prevents overhead from being added to the application.

The rewriting module uses dynamic binary rewriting, based on Dyninst, to rewrite the executing application. Dyninst [BH00] is a C++ based API, which enables program instrumentation. Using the rewriting module, the application is first interrupted by attaching to it. The shared library, containing the optimized function, is then loaded in the executing application's address space. We then direct all calls to function(*func*) to the optimized function(*func optimized*) instead. One trivial way of accomplishing this is by overwriting the first few instructions of *func* with an un-

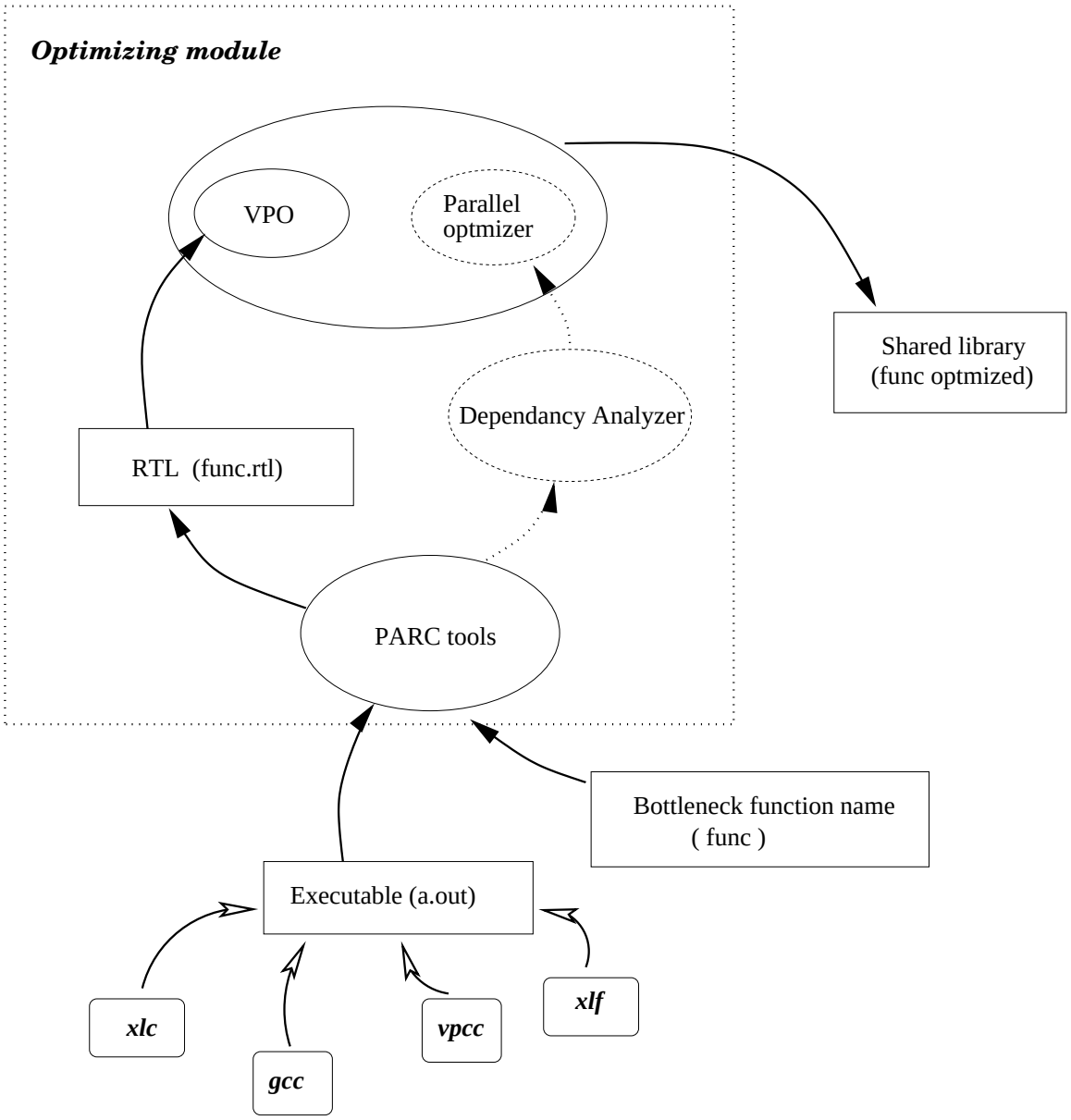

Figure 2.2: Optimizations Module

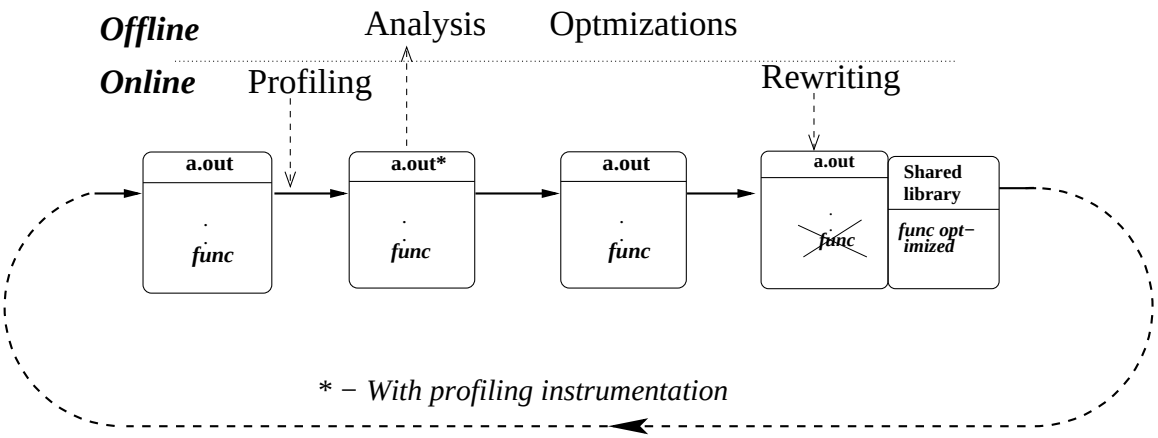

Figure 2.3: Cycle of Optimizations during execution lifetime

conditional jump to *func optimized*. To obtain the addresses of both functions, we exploited the Dyninst API. The rewriting module then detaches from the application and lets it continue. Thus, this online step with respect to the program's execution adds only insignificant overhead. The rewriting module using Dyninst will be explained in detail later on.

This ends the cycle of optimizing one function in the executing application.

To summarize, the lifetime of an application goes through the cycle shown in Figure 2.3.

The application is already executing when it is instrumented to obtain an execution profile. This will collect statistics of the program execution with reference to accesses to components of the memory hierarchy. The statistics generated will be given to the analysis module. This determines the bottleneck function that will be optimized by the optimization module offline. The rewriting module then modifies the application so that the optimized function is used instead of the current function from that point on.

Chapter 3

Optimizing module based on VPCC/VPO

3.1 Background of VPCC/VPO

VPCC/VPO is an optimizing compiler transforming code on machine and language independent representations, yet including machine specific instructions. This allows it to be machine and language independent but still be able to handle machine-specific features. All code improvements are applied to a single low-level representation.

The overall organization of VPCC/VPO is shown in Figure 3.1.

The optimizing compiler is divided into a front-end and a back-end and uses an intermediate language representation in between. The intermediate language representation is in the form of sets of register transfers named as RTL format, [Ben91]. Example of assembly and the corresponding RTL representation :

assembly : lwz 2,32(1)
RTL : +r[2]=R[r[1]+32]

The assembly instruction stands for loading a value at an offset of 32 from contents of register one as base, into register two.

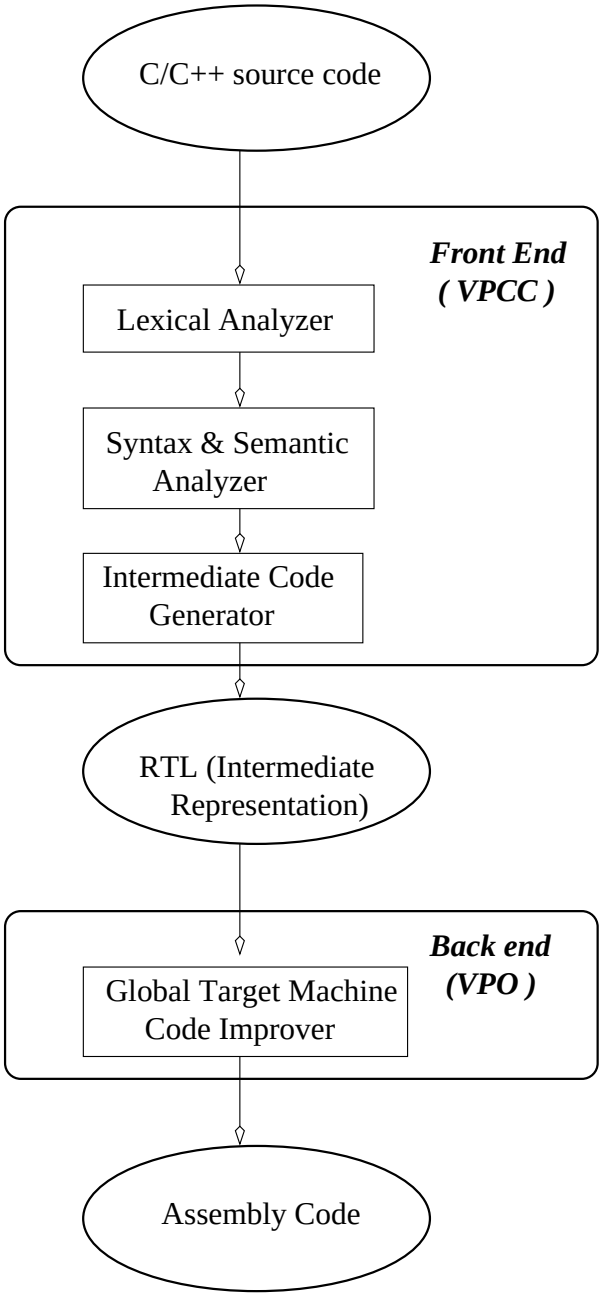

Figure 3.1: VPO based Compiler Architecture

```
procImproveis

BuildControlFlowGraph()
ControlFlowTransformations()
SetLocalLinks()
InstructionSelection()
EvaluationOrderDetermination()
BuildDominatorTree()
FindDominanceFrontiers
LiveVariableAnalysis()
BuildMinimalSSAForm()
SetGlobalLinks()
InstructionSelection()
LiveVariableAnalysisUpdate()
if LocalRegisterAssignment()then
      InstructionSelection()
endif
FindLoops()
EstimateExecutionFrequency()

do
    A = False
    do
        C = False
        LiveVariableAnalysisUpdate()
        A = DeadVariableElimination()
        if ColorLocalVariables() then
                C = InstructionSelection()
                A = True
        endif
    while C

    if A
    then
         C = CommonSubexpressionElimination()
         LiveVariableAnalysisUpdate()
         C = C || DeadVariableElimination()
         C = C || LoopTransformations()
         C = C || InstructionSelection()
         C = C || InlineFunctions()
    endif
while C

ControlFlowTransformations()
Insert FunctionPrologueandEpilogue()
InstructionSelection()
InstructionScheduling()

endproc
```

Figure 3.2: Pseudo code for Optimizations in VPO

The intermediate representation makes the front-end target independent so that it can be used for a variety of target architectures with as little modification as possible. The low-level representation consists of RTLs. The RTL representation is supplied to VPO through a file interface.

The pseudo code for steps carried out during optimization is shown in Figure 3.2.

After reading the RTL file and building necessary internal data structures, a central code improvement routine is invoked per function. First, the control-flow graph is built and control-flow optimizations are performed. Following this, def-use chains are setup by performing local data flow analysis. At this stage, preliminary instruction

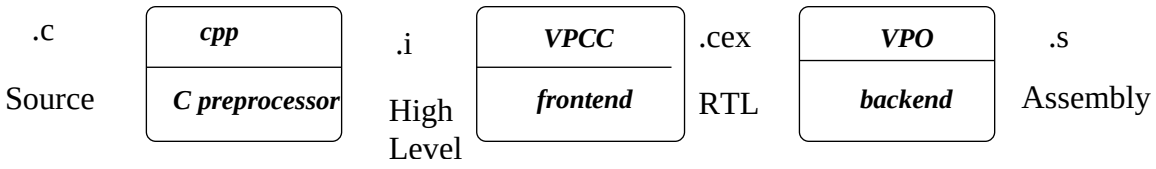

Figure 3.3: File flow through a VPO Compiler

selection is performed. Analysis to build Static Single Assignment(SSA) is performed next, followed by global data flow analysis. Then, instruction selection is re-invoked. At this point, local register allocation is performed. If new hardware registers are allocated, instruction selection is redone

Then loop information is collected. After this, a loop of improvements are applied until the code converges. This includes improvements like common subexpression elimination, loop transformations (induction variable elimination, loop unrolling, ...etc.). After the code converges, control-flow transformations are invoked. Then prologue and epilogue code for the function is generated, and a final pass of instruction selection is performed. If required, an instruction scheduling stage is invoked. Optimizations can be selectively enabled or disabled using command-line options with VPO.

The flow of files through VPCC/VPO is shown in Figure 3.3.

First, the C source code is input to a C preprocessor, such as *cpp*. The preprocessor generates the source in an intermediate format. The intermediate file is given to the VPCC front-end. The front-end generates the file in an encoded form of the RTL representation. This file can be given to the back-end, VPO. VPO generates optimized assembly code for that program.

We ported the VPCC/VPO C optimizing compiler to the POWER architecture. The porting effort is described next.

3.2 Porting of VPCC/VPO to POWER architecture

We implemented two distinct modules: A front-end component that translates the high-level representation to RTL form and a back-end component that translates from RTL to assembly form. The high-level representation is obtained by preprocessing the source code by using any C macro preprocessor.

VPCC/VPO has a very modular structure. It is structured to facilitate porting to a new architecture. The front-end, VPCC, has a machine-independent component called *mip*, which performs lexical, syntactic and semantic analysis. It has a code generator component called *vpo-cgen* that generates output in RTL form. *vpo-cgen* contains a machine-independent component called *lib* and separate machine-dependent components for each architecture (eg., for PowerPC it is called *ppc*). We utilized a version of the VPCC/VPO C compiler for PowerPC architecture that was incomplete. Thus, we had to change the machine-dependent code in order to port the compiler to the POWER architecture. This required changes to the front-end as well as the back-end. The structure of VPCC/VPO is shown in Figure 3.4.

3.2.1 Front end

VPCC uses ART (ASCII Register Transfer) files to generate the RTLs. ART is code embedded by the compiler writer in C source code that facilitates the design and implementation of transformations to generate RTLs by making such code more readable. The language preprocessor, called RTLPREP, translates ART statements into C. There are ART files for all structure elements of the C source code. In the following, the list of ART files is provided:

- *branch.art*: conditional and unconditional jumps
- *call.art*: calls
- *dc.art*: constant declarations

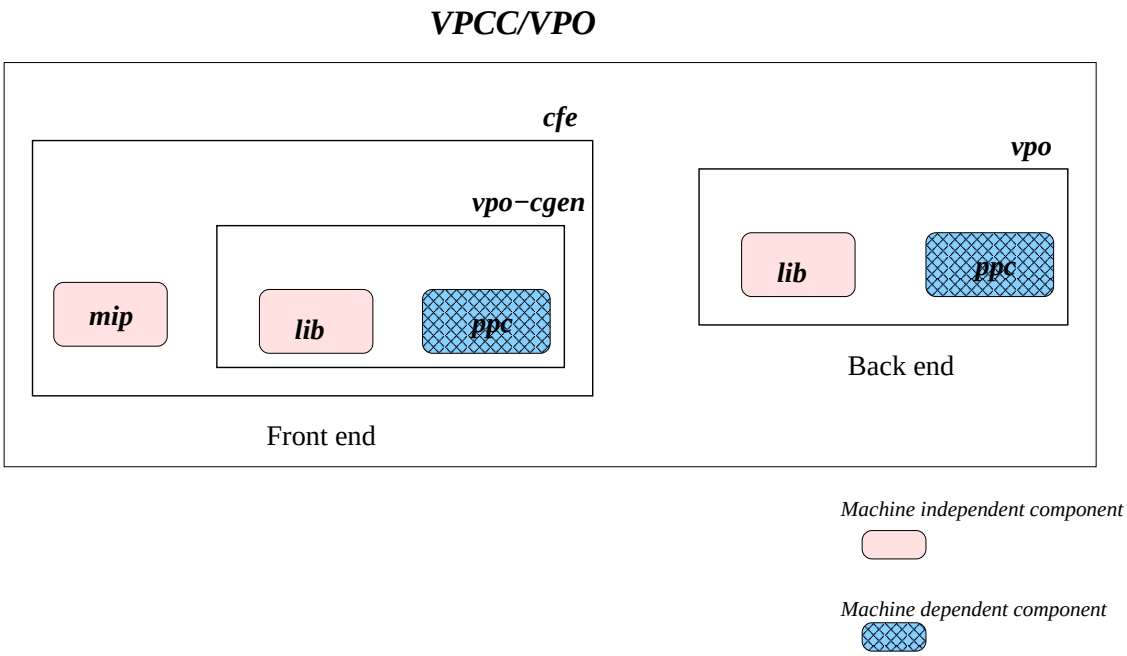

Figure 3.4: VPCC/VPO structure

- *func.art*: function declarations, argument and local declarations and return values
- *field.art*: field manipulations
- *global.art*: global declarations
- *init.art*: build initialization expressions
- *op.art*: binary and unary operations
- *switch.art*: switch statements
- *stmt.art*: manipulation of internal register stack for the front-end
- *struct.art*: structures

For every source code element, we had to generate the appropriate RTL statements using the code in these ART files.

In *call.art*, we had to provide the means for passing arguments to the callee. We used the POWER Assembly Manual [IBM01] as a basic reference. It specifies a fixed set of general-purpose registers (GPRs) and floating-point registers (FPRs) to be used for passing integer and floating-point arguments, respectively. But we found that by restricting ourselves to such conventions, we were failing a test case when we compiled the caller with *vpcc* and callee with the native compiler, *xlc*. When we compiled the caller with *xlc*, we observed that the generated code saved the 8 bytes of the floating-point representation of each floating point argument in 2 GPRs along with its corresponding FPR (each GPR is 4 bytes long as compared to 8 bytes for FPR). Hence, we emitted code to save the bit representation of the floating-point arguments in GPRs.

In *stmt.art*, floating-point constant values were originally declared using the .double assembly mnemonic. The floating-point value was generated in the instruction using printf. The value was truncated depending on the formatting string passed to *printf*. We found this precision error while debugging a test case. We resolved this problem by declaring space for raw bytes representing the floating-point bit pattern using the .long mnemonic. Conversion from integer to floating-point values was also incomplete. We observed the code generated by *xlc* created the bit pattern arithmetically from the integer value. We emitted RTLs to generate the same conversion code.

3.2.2 Back End

The back-end has a machine-independent component called *lib* and a machine dependent component called *ppc*. A register description file in *ppc* specifies the set and types of registers of the target architecture. After we modified this file, we had to modify the machine description file, i.e., a *yacc* grammar file whose action rules serve two purposes - to describe the valid RTLs and to generate assembly instructions when in assembly emission mode. The associated files that describe the action rules were modified in conjunction with the machine description file for each type of statement.

We had to resolve shortcomings of function entry fixup code that needs to be

generated in a callee. We used the assembly manual to properly prepare for function entry and exit points. We had to generate code to find registers to be saved and then generate RTLs to save them. We found that assembly code generated by *xlc* contained instructions to save registers on stack even for register arguments. This is utilized to store the floating-point value representations from the GPRs to the stack space and then perform a floating-point load from that location.

3.2.3 Optimizations

The optimizations in the backend enable us to apply scalar optimizations. In future work, we will implement the component that enables us to apply parallel optimizations based on data dependency and loop information. This would reflect the true benefits of applying dynamic optimizations. Hence, we do not report the measurements of performance gain of applying optimizations using our optimizations module in the current state. We do report results for dynamically utilizing hand-optimized code to an executing application via our rewriting module.

3.2.4 Testing strategy

While we were changing the implementation, we created small test cases to test each functionality we implemented. For example, a test case checked the correctness of passing integer arguments to a function. The strategy we used to test the functionality was to create two files. One was a test file containing in the code, the functionality that we just implemented. The other file was a driver program that called the function in the test file. Both were first compiled using *xlc*, and the output of its execution was saved as a reference. We then linked together the test file compiled with *vpcc* and the driver file compiled with *xlc* and saved the execution output. The two outputs were compared, and the test passed if the outputs matched. After the number of test cases grew, we automated these steps in a script to check all test-file driver-file pairs. We separately tested functionalities of integer and floating-point components as we were working on those components in parallel. The front-end we were working with was a K&R [RJLK78] C front-end. It did not allow ANSI-style function prototypes.

We automated checking of the regression suite, by a script that we could invoke as soon as any change occurred in the compiler. This was frequently used during the development of the PARC tool described in the next section. Other optimizations, such as parallel optimizations dealing with loops and arrays, are beyond the scope of this thesis. They eventually need to be integrated with this framework. The design and implementation realized so far covers scalar optimizations, only.

Chapter 4

PrePARC and PARC Tools

The PrePARC and PARC tools are a set of tools that extract a function from an executable and convert it into RTL form. The PrePARC tool extracts a named function from the disassembly listing of the executable and processes it. PARC takes as input the preprocessed assembly instructions for the function from PrePARC and generates corresponding RTLs.

4.1 PrePARC

The PrePARC tool accepts the disassembly of an executable and the name of the bottleneck function provided by the analysis module. It extracts the function in assembly form and processes it as explained later. The PrePARC tool is written in Perl.

As a first step, PrePARC finds the start of the function in the executable disassembly by locating a label containing the function name. *Objdump*, the disassembler we used, indicates the start of each function by a label containing the function name and the end by an empty line. The tool stores the function disassembly in a vector in the program for later processing.

We need to convert all PC-relative jumps into jumps using labels. This is required as jumps in a linked executable are in the form of jumps by loading an absolute value to the PC (Program Counter). The RTL format requires a label in the source and

target locations. We had to distinguish between jumps and calls as both have a similar representations in the disassembler format:

call ==> 10000170: 48 00 01 99 bl 10000308 <.__mod_init >

jump ==> 1000017c: 41 8a 00 1c beq 2,10000198 <.__start+0x70>

The format above is

"address" : "raw bytes for instruction" "mnemonic form" <"target location in readable form">

Thus, a call can occur only to the start of some function while the target of a branch can occur anywhere within the function at some offset indicated by the plus "+" sign as part of the last field in the disassembly line. Hence, the existence of a plus sign indicates a branch. The target is the last operand of the instruction. We find all branch instructions and their target address values and in every branch instruction, we replace the absolute address from the target with a unique label generated for that offset. An easy way to generate a unique label is to encode the offset value. We modify the jump in the example above into the following instruction:

1000017c: 41 8a 00 1c beq 2, LABEL_0x70

By processing all jump instructions in the first pass, we store all labels that need to be defined and their locations. In the next pass, we prepend labels to the target instructions. Finally, as a last pass, we remove extra fields from each disassembly statement so that just the assembly instructions remain.

PrePARC also adjusts disassembly generated by the disassembler when necessary. For example, there is an optional traceback table after the last instruction of a function in an assembly file. This table provides information related to the function that is used by debuggers to traverse the call stack. A ".long 0x0" assembly instruction separates the end of all instructions and the start of the traceback table following it. The disassembler disassembles the contents of the traceback table incorrectly as instructions. This is corrected by PrePARC in the last pass by locating the ".long 0x0" instruction. From that instruction onwards till the end of the listing, the tool generates data declaration instruction as .long instructions. It uses the byte representation that exists in every disassembly statement. The output of PrePARC is given to PARC, which parses the POWER assembly to generate RTLs.

4.2 PARC

PARC is a parser of POWER assembly based on *lex* [Les75] and *yacc* [Joh79] compilation tools. Its input is the preprocessed assembly listing of a function obtained from PrePARC and its output is the function in RTL format.

4.2.1 Design

A *lex* description for POWER assembly was developed along with a *yacc* grammar whose action-rules generate RTLs corresponding to the assembly statements. The *lex* specification was written by using the POWER assembly manual as a reference. The *lex* specification lists all rules for various mnemonics first. POWER and PowerPC assembly can be used interchangeably for a significant part of the instruction set. Thus, in the *lex* specification we combine alternate (POWER and PowerPC) forms of a mnemonic into the same token. Thus, *fma* and *fmadd* are both converted into *fma* for floating-point addition. Whenever a pseudo-op is seen at the start of a line, the entire line before the newline is returned as a DIRECTIVE token. These are followed in the specification file by rules defining NEWLINE, FUNCNAME and SYMBOL. A FUNCNAME is essentially a SYMBOL preceded by a dot. This is to identify the start of the function assembly to generate a proper function header that contains assembly pseudo-ops like .globl and a .csect. This is data required by the assembler to ensure correct translation. These rules are followed by rules for all numeric constants. We convert all octal, binary and hex numbers into decimal numbers before we process them in PARC, as only decimal numbers are accepted by VPO. These rules are followed by rules specifying a STRING. Various other operators return their identity as tokens. This is followed by empty rule for whitespace and finally a catch-all rule with a do-nothing action for all other characters.

The *yacc* specification describes the input as a series of terminated labeled statements. Each labeled assembly statement can be terminated by a COMMENT, NEWLINE or a semicolon. Each labeled statement itself is an assembly statement with an optional label at the start. All assembly statements are grouped into the following types of

assembly statements:

- load, store, immed(immediate mode operations), binop, compare, uncondbranch, condbranch, condbranchlr (conditional branch to target present in the link register), move (for movement to and from special registers).

All DIRECTIVEs are classified as POWER assembly statements and are emitted as RTLs containing assembly statements by prepending the statement with a '-' character. A '-' character at the start indicates to VPCC that this RTL contains an assembly statement that needs to be emitted without further processing. Two groups of operands are used:

- twoconstant, which contains two operands named as source and destination.
- basedisplacement, which contains three integer operands termed as destination, base, and displacement.

All loads and stores use basedisplacement or base16bitdisplacement, where the latter is equivalent to basedisplacement with an additional check to confirm that the displacement does not exceed 16 bits. This is for instructions that require the displacement operand to be limited to a 16 bit value. In immed statement, we handle CISC-like instructions such as xoriu ("xor immediate a 16 bit value with the upper 16 bits of the source register and place it in a destination register"). These have no corresponding RTL statements and are converted into a set of RTLs having the same effect. For example, xoriu becomes "store immediate value in a temporary register, xor registers, followed by shift left by 16 bits and place the result in the destination". These multiple RTLs may use temporary registers that will be ultimately assigned by the register allocator in VPCC. Later, a peephole pattern in VPO will detect these sets of statements and convert them back to the complex instruction. By not denoting them explicitly, we reduce the complexity of the subset of RTLs accepted as input to VPO. In branch statements, we encounter various extended mnemonics. These are mnemonics that imply a base mnemonic and specific values for operands. For example,

bge <target address> implies

bc 4,0, <target address>

where bc is branch on condition, 4 indicates branch if the condition bit is false and 0 indicates that the condition bit to be checked is the less-than bit. Also, a call instruction is similar to a jump where the link register bit in the instruction is set. For calls, we needed to generate associated RTL lines including RTLs indicating used and trashed registers.

4.2.2 Issues

In the existing PowerPC version of *branch.art*, the comparison-and-branch model had a single RTL line for comparing two registers and branching conditionally to a target. These were converted by the back-end into 2 assembly instructions. The first instruction sets a bit in the Condition Register and the second instruction branches conditionally depending on the bit set to the target label. While looking at the disassembly in the PARC tool, we would need to combine those 2 assembly statements together into one RTL. That would require us to remember the last comparison made prior to the branch instruction to generate the combined RTL. We changed the RTL model to split the original RTL into separate comparison and branch RTL statements. For this, a condition register was introduced in the register model in the POWER back-end of VPO. This register is set in the comparison instruction. In the branch instruction, the type of comparison used in the RTL would reflect the bit encoding from the original assembly instruction for the bit that is checked for making the jump decision.

For example, if the assembly instruction were

bc 12,0,Here - (Jump to Here if less than bit is set)

This would be translated to the following RTL:

+PC=CR<1,Here

where 1 is a dummy value.

The flow of files in the optimizing module is shown in Figure 4.1.

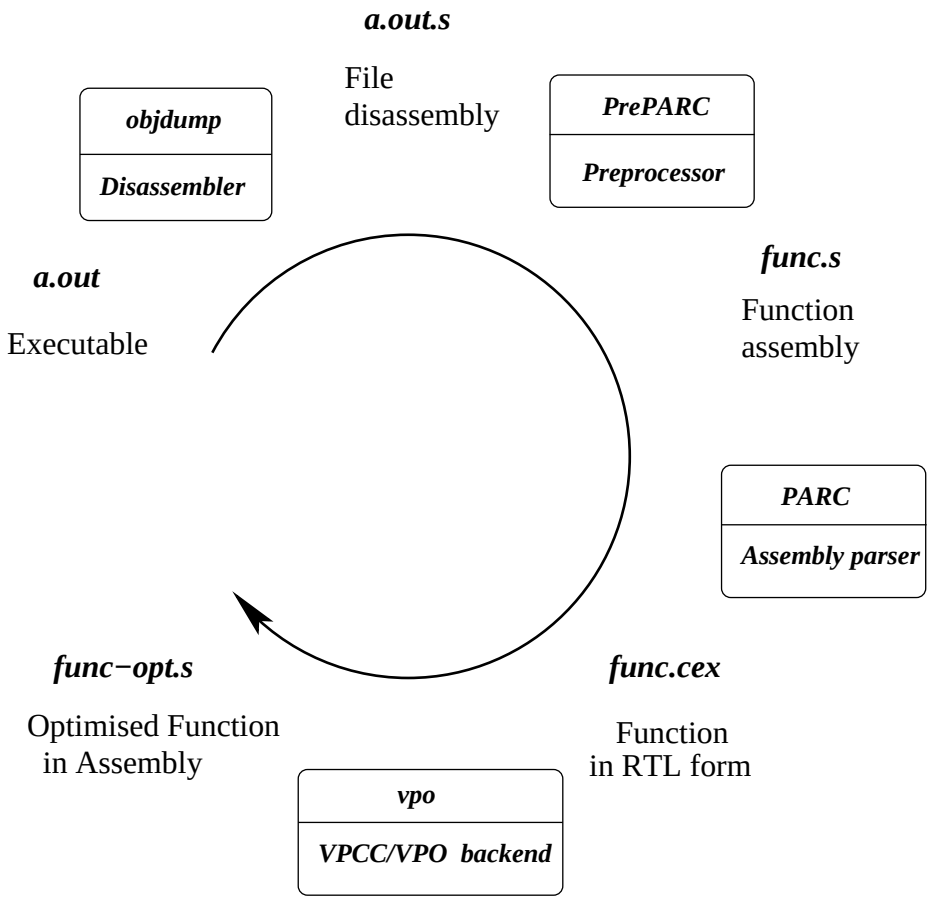

Figure 4.1: File Flow through tool chain

The disassembler, *objdump*, accepts the executable and outputs the disassembly for the entire executable. This is input to the PrePARC, which outputs the pre-processed assembly listing for the function. PARC accepts the function assembly and outputs the function in RTL form to VPO. VPO finally generates the optimized function in assembly form.

Chapter 5

On-the-fly Rewriting module

In this chapter, we discuss the design of the rewriting framework. First, we give a background on dynamic binary rewriting in brief. We then describe the dynamic binary rewriting API used. Finally, we describe our rewriting module that enables us to hot-swap a function while the application is executing.

5.1 Dynamic Binary Rewriting & Dyninst

Binary rewriting refers to post-link time modification of an executable, i.e., modification of the application's binary representation before executing the program [SW92]. Binary translation, on the other hand, represents the process of modifying the instructions or the data of an application while its executing [BDB00]. Examples include Transmeta's Code Morph project [CSG+97] that allows x86 programs to run on low-power VLIW Crusoe processors. Dynamic binary rewriting is a combination of these techniques that uses a control process to rewrite the binary representation of an executing process. Dynamic binary rewriting is used because of its following advantages:

- It can capture memory references of the entire application, including those of pre-compiled library routines. It is difficult for static approaches to obtain memory reference information for pre-compiled library routines due to unavailability of source code. This is not an issue for dynamic binary rewriting as it does not depend on source code but utilizes runtime information.

- It can accommodate mixed-language applications, which is crucial as numerous scientific production codes use a combination of different source languages.

- It also provides potential to use runtime information to optimize for input dependencies, application modes and user behavior. These provide opportunities to yield performance gains beyond static code optimization without profile-guided feedback, though this will be considered only in future work.

We use Dyninst to apply dynamic binary rewriting. Dyninst [BH00] is a C++ API that permits instrumentation and modification of an executing application. It allows machine-independent binary instrumentation programs to be expressed. Dyninst is based on abstractions of a program and its state while in execution. The two primary abstractions are points and snippets. Point is a location in a program where instrumentation can be inserted. A snippet is a representation of instrumentation code to be inserted at a point in a program. For example, to count the number of times a function is called, we can insert instrumentation at the entry point of the function, which increments a counter. The first instruction of the procedure is the "point". A "snippet" is used to create the statement to increment the counter. Snippets can include function calls, expressions and loops. The overall structure of code instrumentation is shown in Figure 5.1.

There are two processes - the mutator (containing Dyninst API calls) and the mutatee (the executing program to be dynamically rewritten). The mutator also contains the runtime compiler and the utility routines to manipulate the application process. The mutatee, as shown on the right side of the figure, contains the original code in the top half of the figure. The bottom half contains the snippets that are inserted into the program as well as the runtime library that implements the Dyninst API. The API is based on following classes:

- BPatch_thread is used to control code in execution (start, stop or terminate threads). It allows one to insert instrumentation code in the program.

- BPatch_image represents the program executable.

- BPatch_function represents a function in the application.

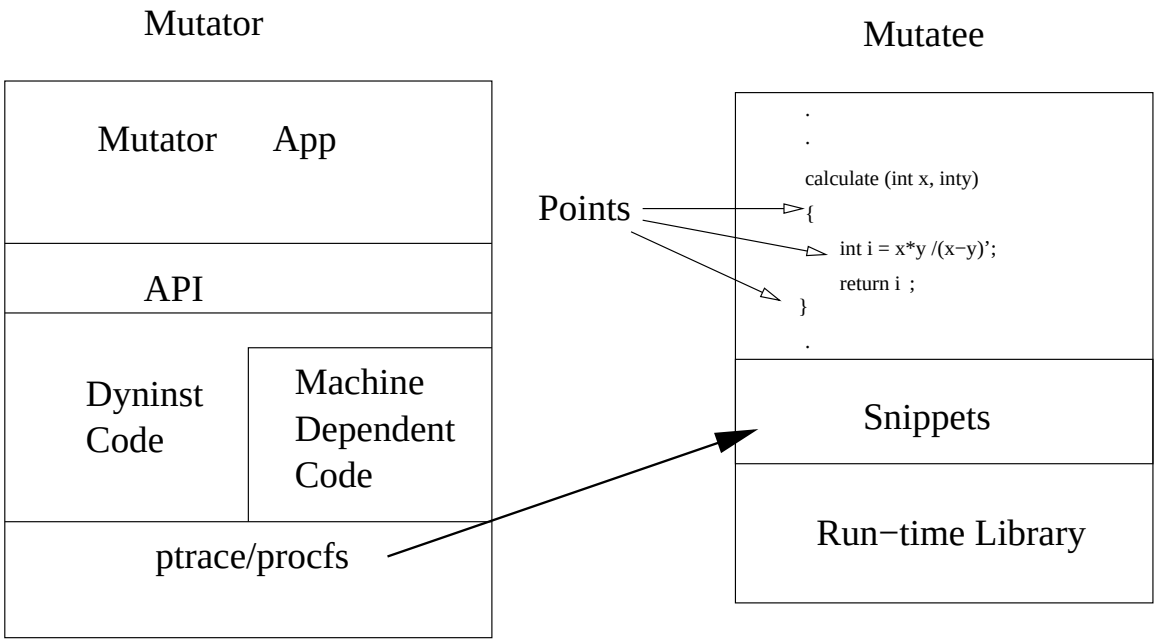

Figure 5.1: Dyninst Programs Structure

```
Function replace (/* takes as input the address of the old and new function*/) {

   //0.Write in the first location of the instruction array, loading into register
        r0 the address of the new function

   //1. move r0 to ctr register

   //2. branch to ctr (bcctr), fixed hex pattern

   //3  Write the instruction array at address beginning at the function entry
      point of the old function.

}//end func

Main function ( /*  Accepts the name of the executable,the process id of the
  application, the names of the bottleneck and the optimized function*/

   //4  Get a thread object by attaching  to the process

   //5  Load the library containing the optimized function in the process address  space

   //6  Find function objects for the old and new function names

   //7  Get process call stack

   //8  For every function on the stack, store the program counter and execute step 9.

   //9 Check if the Program counter is within the address range which will be overwritten. If yes goto step 10

   //10 Detach from the application and exit

   //11 Call function myreplace with addresses of the old and the new functions

   //12 Detach from the application and let it continue

  }/* end main */
```

Figure 5.2: Mutator Program

- BPatch_point is a location in the code where the library can insert instrumentation. Points can be described symbolically, eg., as the start of a function or by providing a virtual address.

5.2 Our Mutator program

A brief outline of our mutator program is shown in Figure 5.2.

In the main function, we pass the executable path and the process id of the

execution instance followed by the name of the unoptimized function and the name of the optimized version of the function. In line 4, we obtain a Dyninst thread object, which acts as a handle to the executing application. This is achieved by a Dyninst call that attaches to the application, identified by the process id and the executable name, and interrupts it. The thread object is later used to insert instrumentation. In line 5, we load the shared library containing the optimized version of the function in the application's address space. In line 6, we obtain Dyninst function objects for the unoptimized (old) function and the optimized (new) function versions. These objects are used to get the function start addresses passed in line 11 to function *myreplace*. *myreplace* will ensure that calls to the old function lead to the new function code being executed. Before that, we check (lines 7-10) if the Program Counter in the entire current call-stack does not lie in the region where will be inserting our instrumentation. If so, we do nothing and exit. Else, we reach line 11 where we call *myreplace*, passing the addresses of the unoptimized and optimized versions of the function. In function *myreplace*, we create a set of instructions to make an unconditional jump to the new function address. This is done using 3 instructions. First, at line 0, we load the address of the optimized function into GPR r0. We then add an instruction to move r0 to Counter register, ctr in line 1. We then add an instruction to branch to the address in the Counter register in line 2. Finally, in line 3, we write these instructions at the address beginning at the start of the old (unoptimized) function. Thus, the rewriting module will lead the unoptimized function to a jump to the optimized function within the shared library dynamically loaded.

Chapter 6

Validation Experiments

We demonstrate, in the absence of our optimizing module to include parallel optimizations, the capability of dynamic binary rewriting to obtain considerable performance improvements.

We use five synthetic application benchmarks. In each benchmark, we execute a function multiple times. Initially, we let the unoptimized version of the function execute. We then run our mutator program to modify the application such that calls to the original function lead to the newly optimized function code. Each time the wall clock time obtained in the last call is reported.

The first two benchmarks were obtained from [MM03].

The first benchmark performs matrix multiplication in the function. The original executable contains a function with a simple matrix multiply loop for a matrix of dimensions 800 by 800. The optimized version of the same matrix multiply function uses tiling [WL91, Wol89].

The second benchmark performs Erlebacher ADI integration. The optimized version of the function is obtained by applying loop interchange and loop fusion.

The third benchmark performs encryption/decryption using Skipjack [Nat98]. The optimized version of the algorithm uses loop unrolling and data-layout modification. The third benchmark was obtained from implementations by Mark Tillotson < markt@chaos.org.uk> and Paul Rissanen <bande@lut.fi>.

LINPACK, [Don87], is the fourth benchmark. The optimized version was obtained

Table 6.1: Proof-of-concept Experiment data

Benchmark		Mean time per call (sec)	Standard Deviation(sec)
Matrix Multiplication	Unoptimized	33.0000	0.0000
	Optimized	12.6667	0.5773
Erlebacher ADI	Unoptimized	6.2733	0.0493
	Optimized	0.4367	0.0058
Skipjack	Unoptimized	0.1067	0.0058
	Optimized	0.0200	0.0000
Linpack	Unoptimized	0.3687	0.0015
	Optimized	0.2500	0.0010
fm-part	Unoptimized	0.0207	0.0006
	Optimized	0.0120	0.0010

by applying common subexpression elimination.

The fifth benchmark is a test case from our regression test suite named fm-part, which is a hypergraph partioning program. The optimized version was obtained by compiling it with all optimizations available.

The mean execution timings are shown in the Table 6.1. Thus, we see potential for considerable improvements in performance of up to an order of a magnitude using dynamic optimizations.

The time taken for the rewriting step over all experiments had a mean value of 502.91 milliseconds and a standard deviation of 3.08 milliseconds. Thus the execution overhead of rewriting can be recouped over the entire execution duration when savings for calls to the optimized function are accumulated.

A compiler can statically perform optimizations like tiling if it knows details of the underlying architecture. Still, pre-compiled code containing this optimization may not be suited to all architectures on which the code is deployed. Also, optimizations like loop unrolling and data-layout modifications may require knowledge of memory performance data, which is easily available to a dynamic optimizing compiler. Although any compiler can statically apply common subexpression elimination, a dynamically optimizing compiler gives the user the option of applying it to pre-compiled code where it was not applied already.

Chapter 7

Discussion

We discuss various benefits and limitations in our approach in this section.

We use dynamic optimizations to improve performance of executing applications and mainly target long-running parallel applications. Optimizations are applied to the code from the executable form without any dependence on the source code. Thus, we can target precompiled library code as well as mixed language code. But this means we need to derive high-level information that is easy to derive from the source code. In order to apply parallel optimizations, we need to derive loop and data dependence information from the executable. This is a difficult problem that needs to be solved.

The tradeoff between benefits and costs of applying dynamic optimizations needs to be considered. In dynamic optimizations, the execution overhead costs of applying optimizations needs to be recouped by the performance gains of applying optimizations. We derive performance statistics by modifying the application to generate memory access statistics. This adds a small amount of execution overhead that we minimize by a number of ways. We use binary manipulation to add profile-generating instrumentation and then remove it after a period of time so that the extent of time that the application suffers execution overhead is small. We also analyze the statistics offline to avoid any further overhead. We interrupt the application to add optimized code and modify the application to make it utilize the optimized code. The execution overhead this step adds is insignificant.

We also continue to derive benefits from applying optimization to any subsequent

execution, which is often significant for long-running parallel applications. Lastly, the cycle of optimizing a bottleneck function can be repeated over and over again till the application terminates, which provides significant potential for extracting performance gains. This is crucial, as the existing code could be derived from a compiler that optimizes code itself. Thus, we need to derive as much potential to apply optimizations as possible. This is achieved by optimizing code that is a performance bottleneck in the current execution scenario.

Chapter 8

Related Work

Dynamo [BDB00] is based on dynamic compilation. It has a staged compilation model for achieving lightweight and heavyweight optimizations where different modules of the input are compiled into various levels of representation. Higher-level representations are used for modules that would benefit from "heavyweight" optimizations and decreasing levels are used for optimizations with decreasing costs. Dynamic optimization using edge-counting profiling is available. Like our scheme, it uses profiling only for a portion of the program run. Their primary focus is virtual machines.

In Continuous Program Optimization [KF01], Kistler and Franz also generate an intermediate GSA (guarded static single assignment) format for optimizations. They use a continuous profiler and a background optimizer and hot-swap optimized functions. They report that profiling costs are more than the optimization benefits for some optimizations so that they cannot apply dynamic optimizations to all functions. In our approach, we use dynamic instrumentation to insert and remove profiling code at intervals so that we do not incur the overhead of profiling during the entire execution. They provide another insight that continuous optimization rather than one-time optimization provides increased performance benefit. This is because the same application can be put to different uses at different points of time depending on program input and different execution scenarios. Thus, the same application may provide different opportunities for optimizations at different points in its execution. Also, the same library optimized for a particular application gives significant performance gains

over optimizations applied to same library for a different application. This is another case for dynamic optimization.

OM [SW92] has a similar approach to ours that it takes as input an executable, builds the intermediate RTL format and then applies optimizations before generating object code. However, all steps are executed offline such that optimizations are performed between two execution runs. Also, they do not collect any profile to decide which functions need to be optimized.

The PLTO (Pentium link time optimizer) from the SOLAR project [SDA01] also uses binary rewriting to optimize procedures, but it performs optimizations online. It first collects an execution profile on training input and then optimizes the execution disassembly offline. The optimized program is utilized in the next execution run. We do not use training input but obtain profile information from actual execution. The authors report large speedups in integer programs that indicates potential for code optimization in statically optimized compiled code.

Mojo [CLCG00] targets dynamic optimization for a CISC (x86) architecture with support for large multi-threaded desktop applications that use exception handling. It counts the frequency of execution to identify hot-spot functions. These are then disassembled and optimized online. There is a controller thread that decides where program control should be transferred depending on whether optimized code exists or not. The performance gain observed was not significant. One reason could be the large execution overheads for the entire process being online.

Jalapeño [GAH+00] is a virtual machine implementation that includes adaptive feedback-oriented optimizations. The adaptive optimization subsystem invokes the optimizing compiler when profiling data suggests that recompiling a method with additional optimizations may be beneficial. The adaptive optimization system consists of various systems internally. A runtime measurement system gathers information about executing methods. There are separate systems that collect raw performance data using a variety of techniques, such as hardware performance counters and compiler-inserted instrumentation. There are separate threads that analyze the data collected. The recompilation system decides which optimizations to apply using the previous data collected. As compared to our architecture, all operations are

performed online, which increases the cost of optimization. Similar to many other systems, it uses a cost-benefit analysis to decide whether a module needs recompilation with additional optimizations.

Strata [SD01] is an infrastructure for building software dynamic translators that can be re-targeted easily and be flexible enough to enable performance improvement as well as meet other objectives such as the construction of instruction-set simulators [CK93] or low-cost simulation of new OS or architecture features [Dit00], [UC00]. It is organized as a virtual machine where Strata itself examines and translates instructions before they are executed on the host machine. It can examine windows of instructions called fragments that can potentially span across function calls. Strata can implement optimizations like instruction scheduling.

The Morph system [CSG+97] provides a framework for the automatic collection and management of profile information and application of profile-driven optimizations. It uses an operating system kernel component that implements continuous, low overhead profiling and program monitoring. Similar to our approach, they separate the analysis of a profile collected in an offline manner, but, unlike ours, they collect profile information continuously. There is a compiler component that implements re-optimization and, similar to our approach, it does not require source code.

Digital's FX!32 [CH01] is similar to Morph in that execution profiles of x86 Win32 applications are continuously collected and fed to a background process that translates the previously emulated portions of x86 binaries into native code transparent to the user. But it collects profile samples during program emulation and it focuses on code translation than code optimization.

Dyninst [BH00] is a C++ based API that permits the insertion of code into a running program. The goal of this API is to provide a machine independent interface to permit the creation of tools and applications that use runtime code patching. Applications that can make use of this dynamic code adaptation system include performance measurement tools, correctness debuggers, execution drive simulations and computational steering. Dyninst is based on the idea of dynamic instrumentation technology [JKHC94] developed as a part of the Paradyn Parallel Performance Tools Project [MCC+95].

Paradyn is a performance measurement tool for parallel and distributed programs. It automates most of the steps for the search of performance bottlenecks. It inserts instrumentation onto executing applications that extracts execution information and searches for performance problems online. It searches for problems using a performance model that contains hypotheses for types of problems that occur in parallel programs. It controls its instrumentation overhead by monitoring the cost of its data-collection, limiting the instrumentation to a (user controllable) threshold.

Chapter 9

Conclusions and Future Work

We have described various components of a dynamic optimization framework designed to improve performance of long running-parallel applications. We have developed a framework to identify and extract functions that are performance bottlenecks, apply scalar optimizations and reinsert the optimized function in an executing application. We are able to optimize code from the binary representation. We prove a proof-of-concept of the rewriting module of our framework using synthetic benchmarks. Future work includes a component to perform parallel optimizations within the existing framework. For the same purpose, we also need to derive data flow, induction variables and data dependency information from the executable. We also plan to extend this optimization framework for distributed and shared memory execution based on MPI [For94] & OpenMP [CMD+01]. We are considering the use of DPCL [HDH01], i.e., a Dyninst-based tool that allows binary manipulation on a set of processes on one or more computing nodes.

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