DYNAMIC COMPILER OPTIMIZATION TECHNIQUES FOR MATLAB

by

Nurudeen Abiodun Lameed

School of Computer Science
McGill University, Montréal

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Abstract

MATLAB has gained widespread acceptance among engineers and scientists. Several aspects of the language such as dynamic loading and typing, safe updates, copy semantics for arrays, and support for higher-order functions contribute to its appeal, but at the same time provide many challenges to the compiler and virtual machine. MATLAB is a dynamic language. Traditional implementations of the language use interpreters and have been found to be too slow for large computations. More recently, researchers and software developers have been developing JIT compilers for MATLAB and other dynamic languages. This thesis is about the development of new compiler analyses and transformations for a MATLAB JIT compiler, McJIT, which is based on the LLVM JIT compiler toolkit.

The new contributions include a collection of novel analyses for optimizing copying of arrays, which are performed when a function is first compiled. We designed and implemented four analyses to support an efficient implementation of array copy semantics in a MATLAB JIT compiler. Experimental results show that copy optimization is essential for performance improvement in a compiler for the MATLAB language.

We also developed a variety of new dynamic analyses and code transformations for optimizing running code on-the-fly according to the current conditions of the runtime environment. LLVM does not currently support on-the-fly code transformation. So, we first developed a new on-stack replacement approach for LLVM. This capability allows the runtime stack to be modified during the execution of a function, thus enabling a continuation of the execution at a higher optimization level. We then used the on-stack replacement implementation to support selective inlining of function calls in long-running loops. Our experimental results show that function calls in long-running loops can result in high runtime overhead, and that selective dynamic inlining can be used to drastically reduce this

overhead.

The built-in function `feval` is an important MATLAB feature for certain classes of numerical programs and solvers which benefit from having functions as parameters. Programmers may pass a function name or function handle to the solver and then the solver uses `feval` to indirectly call the function. In this thesis, we show that although `feval` provides an acceptable abstraction mechanism for these types of applications, there are significant performance overheads for function calls via `feval`, in both MATLAB interpreters and JITs. The thesis then proposes, implements and compares two on-the-fly mechanisms for specialization of `feval` calls. The first approach uses our on-stack replacement technology. The second approach specializes calls of functions with `feval` using a combination of runtime input argument types and values. Experimental results on seven numerical solvers show that the techniques provide good performance improvements.

The implementation of all the analyses and code transformations presented in this thesis has been done within the McLab virtual machine, McVM, and is available to the public as open source software.

Résumé

MATLAB est devenu reconnu parmi les ingénieurs et les scientifiques. Plusieurs aspects du langage comme le chargement et le typage dynamique, la mise à jour sûr, la sémantique de copie pour les tableaux, et le support des fonctions d'ordre supérieur contribuent à son attrait, mais induisent de nombreuses difficultés pour les compilateurs et les machines virtuelles. MATLAB est un langage dynamique. Les implémentations classiques du langage fonctionnent grâce à des interpréteurs et sont généralement trop lentes pour des larges calculs. Plus récemment, les chercheurs ainsi que les programmeurs ont développé des compilateurs JIT pour MATLAB et d'autres langages dynamiques. Cette thèse traite le développement de nouvelles analyses et transformations pour un compilateur JIT MATLAB, McJIT, qui est basé sur l'outil LLVM.

Ces nouvelles contributions comprennent plusieurs analyses novatrices pour optimiser la copie de tableaux, qui sont exécutées quand une fonction est compilée pour la première fois. Nous avons implémenté quatre analyses pour permettre une implémentation efficace de la sémantique de copie de tableaux dans un compilateur JIT MATLAB. Les résultats expérimentaux montrent que l'optimisation de la copie est essentielle pour améliorer les performances dans un compilateur pour le langage MATLAB.

Nous avons aussi développé une variété d'analyses dynamiques novatrices et des transformations de code pour optimiser du code à la volée en fonction de l'environnement d'exécution. Actuellement, LLVM ne supporte pas les transformations de code à la volée. En conséquence, nous avons d'abord développé une nouvelle approche pour faire du remplacement sur la pile avec LLVM. Cette fonctionnalité permet à la pile d'exécution d'être modifiée pendant l'exécution de la fonction, ce qui permet de continuer l'exécution à un niveau supérieur d'optimisation. Nous avons ensuite utilisé cette implémentation du remplacement sur la pile pour permettre l'en line des appels de fonctions dans les boucles. Nos résultats expérimentaux montrent que les appels de fonctions dans les boucles à long temps d'exécution peuvent induire un coût important en termes de performances, et que l'en line

dynamique et sélectif peut être utilisé pour réduire drastiquement ce coût.

La fonction ”feval” est une fonctionnalité importante de MATLAB pour certains programmes de calcul numérique qui profitent de la possibilité de passer des fonctions comme paramètres. Les programmeurs peuvent passer le nom d'une fonction ou un pointeur de fonctions à un programme qui utilisera ensuite feval pour appeler indirectement cette fonction. Dans cette thèse, nous montrons que malgré le fait que feval soit un mécanisme d'abstraction appréciable pour certaines applications, il induit un coût significatif, à la fois pour les interpréteurs et pour les compilateurs JIT. Cette thèse propose, implémente et compare deux mécanismes à la volée pour la spécialisation des appels utilisant feval. La première méthode utilise notre mécanisme de remplacement sur la pile. La seconde méthode spécialise les appels de fonctions utilisant feval en combinant le type et la valeur des arguments à l'exécution. Les résultats expérimentaux sur sept programmes différents montrent que ces techniques permettent une bonne amélioration des performances.

L'implémentation de toute les analyses et transformations de code présentées dans cette thèse a été effectué dans la machine virtuelle McLab, appelée McVM, et est disponible au public en tant que logiciel libre.

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Contents

Listings

List of Figures

List of Tables

List of Abbreviations

AST abstract syntax tree

CFG control flow graph

IR intermediate representation

JIT just-in-time

JVM Java virtual machine

OSR on-stack replacement

RC reference-counting

SSA static single assignment

VM virtual machine

Chapter 1
Introduction

Almost anyone using a computing device today has used a program written in a dynamic language. A large proportion of Internet applications are developed with dynamic languages. JavaScript, Perl, PHP, Python, Ruby, and MATLAB® [1] are some of the widely used dynamic languages. They shared a common property: they are dynamically typed. Their dynamic nature contributes to their appeal. But it also contributes to their compilation difficulty. Thus, they are mostly interpreted, and programs written in any of them often run slower than those written in a static language such as C.

The MATLAB programming language is a dynamic array-based language that is popular among engineers and scientists. It was designed for sophisticated matrix and vector operations, which are common in scientific applications. The MATLAB programming language is an important language with a simple syntax. It is being used in different computing domains. By the year 2004, the number of MATLAB users had exceeded one million. Further, much like the way transistor growth in microprocessor design has obeyed the famous Moore's law [Moo65], the number of users of the MATLAB language doubled about every two years between 1984 and 2004, and continues to increase.

The dynamic nature of the MATLAB language, together with its simple syntax, aids rapid software development by helping programmers to reason about their programs. The combination, however, poses serious compilation and performance challenges. Dynamic

1. http://www.mathworks.com/products/pfo/.

language features such as dynamic function loading causes the compiler to delay most optimizations until run time. This increases runtime overhead.

Traditional implementations of the MATLAB programming language are based on interpreters [gnu12, The02]. They are generally considered to be too slow for long-running MATLAB programs. Recently, researchers and developers have been developing virtual machines and just-in-time compilers [AP02, The02, CB09, CBHV10] for the MATLAB language. There remain, however, important compilation challenges. Although the dynamic nature of the MATLAB language provides challenges to runtime optimizations, it also presents great opportunities. For example, the runtime behaviour of a MATLAB program can be observed to discover opportunities for optimization and an on-the-fly optimizer can dynamically apply suitable optimizations that benefit from the identified opportunities.

This thesis is about the development of a collection of novel techniques for on-the-fly transformations and optimizations in JIT compilers for the MATLAB language. We show how to use runtime information about program behaviour to support transformations and optimizations that can improve the performance of virtual machines and JIT compilers for the MATLAB programming language.

We begin this chapter of the thesis with an introduction to virtual machines and JIT compilers. Later, we briefly review a study that further motivates our research work. We then highlight the challenges and our solutions that address the challenges. Further, we summarize our main research contributions. We conclude the chapter with the organization of the remaining chapters of the thesis.

1.1 Virtual Machines

The increasing growth of the Internet is driving a growing interest in virtualization among hardware designers, operating system designers, programming language designers, and compiler writers. In many systems, virtualization has helped to achieve cross-platform independence, inter-operability (i.e., high-level language independence), security, and cross-platform performance. In the past, the main motivation for building virtual machines was to run different operating systems on shared hardware. This was necessary to

support different computational needs of different group of users on shared hardware.

Virtual machines provided a transformation of the single interface of a computer system into many *virtual* interfaces [Gol73, PG74]. Each interface behaves like a complete computer system that is composed of an operating system and support many simultaneous user processes. Hence, they are called *system* virtual machines [SN05].

A *process* virtual machine supports only a single process. Virtual machines for high-level languages (e.g., McVM, JVM [LY99], and CLR [Int13]) are process virtual machines. They are typically designed to provide platform independence by reconciling differences in architectures and operating systems. In this thesis, we are concerned only with implementations of process virtual machines.

A system's interface is specified by its instruction set architecture (ISA). Virtual machines are implemented by emulating the instruction set of one system — the *source* — on a machine with a different instruction set — the *target*. A process virtual machine provides a machine-independent interface that is similar to a conventional machine instruction set architecture. The ISA of a virtual machine is called virtual instruction set architecture (V-ISA).

Many V-ISAs have been designed. *P-code* [NAJ+75] is a V-ISA for the Pascal machine; similarly, *Java byte codes* is a V-ISA for the Java virtual machine. Microsoft intermediate language (MSIL) (or common intermediate language (CLI) for Microsoft's common language infrastructure (CLI)) [Int13] and LLVM [LA04] are more general V-ISAs.

The virtual instruction set of a virtual machine can be interpreted or compiled. This thesis concentrates on JIT compilation techniques.

1.1.1 JIT Compilation

Compilation concerns the translation of one language into another language. A special translation technique used in implementing virtual machines is the JIT (Just-In-Time) compilation technique. JIT compilation is an old technique. It was developed in response to the performance challenges of the interpretation techniques used in implementing virtual machines.

Instead of interpreting virtual instructions, some blocks of code are now compiled just before they are executed. Thus repeated execution of the same code requires no further interpretation or compilation. This approach combines the benefits of static compilation: compiled code generally runs faster than interpreted code. It also brings the benefits of interpretation because the compilation process can benefit from semantic and runtime information. According to Aycock [Ayc03], McCarthy's paper on LISP [McC60] is the first published work on JIT compilation. Several techniques for JIT compilation of object-oriented languages were developed in several implementations of Smalltalk [GR83, DS84a, Kay93], SELF [Cha92], and, more recently, in many implementations of Java virtual machines [ATCL+98, YMP+99, Kra98, CLS00, PVC01, SOK+04, AAB+05].

Some virtual machines have interpreters and JIT compilers. Some other VMs begin with a base-line compiler and recompile methods or functions with a more optimizing compiler after identifying some frequently executed methods or code regions — the *hot* spots. The optimizing compiler often performs a range of optimizations, including, traditional optimizations such as register allocation, inlining, common sub-expression elimination, and other runtime optimization tailored to exploit some relevant runtime information.

McVM [CBHV10] is a recent virtual machine developed for the MATLAB language. It has a basic interpreter and an optimizing JIT compiler that is supported by the LLVM [LA04] compiler framework. We introduce the MATLAB language, McVM and LLVM in Chapter 2.

1.2 Motivation

Over the years, numerous MATLAB programs have been developed to solve a variety of problems in different domains, in particular the numerical computing domain. To gain some insight into the way different MATLAB programmers use the features of the MATLAB language, a study of MATLAB programs is necessary. This will help in the identification of the important features in MATLAB programs; further, it may also reveal some major sources of overhead. In this section, we describe a study conducted on a large collection of MATLAB programs.

1.2.1 Characteristics of MATLAB Programs

To discover the common characteristics of MATLAB programs, we conducted a study of a large collection of MATLAB programs. [2] The result of this study is shown in Table 1.1. Out of 12,946 functions in 3,114 files examined, 31% (3,992) contain loops; 41% (4,356) of the loops contain conditional statements while 62% (6,681) of the loops have function calls. About 95% (12,270) of the functions have one or more input parameters while 54% (6,954) have one or more output parameters.

The results of this study provide a guide to the identification of key optimizations that address many of the compilation and performance challenges in a MATLAB compiler. we examine the challenges and opportunities in MATLAB programs in the next section.

Property	**Count**
Number of files	3,114
Number of functions	12,946
Number of functions with input parameters	12,270
Number of functions with output parameters	6,954
Number of functions with both input and output parameters	6,664
Number of functions with loops	3,992
Number of loops	10,726
Number of loops with conditionals	4,356
Number of loops with calls	6,681

Table 1.1 – Some characteristics of MATLAB programs

1.3 Challenges

A typical MATLAB program operates on large arrays. Although many of these operations are difficult to compile efficiently, static and dynamic optimization opportunities exist.

2. These MATLAB programs were collected from a variety of sources, including those from: `http://www.mathworks.com/matlabcentral/fileexchange`, `http://people.sc.fsu.edu/~jburkardt/m_src/m_src.html`, `http://www.csse.uwa.edu.au/~pk/Research/MatlabFns/` and `http://www.mathtools.net/MATLAB/`.

In this section, we highlight some performance challenges and optimization opportunities in MATLAB programs.

1.3.1 Challenge 1: Copy Semantics

The use of copy semantics for array assignments, for parameter passing and for returning values from a function is one of the cases where the simple semantics of the MATLAB language helps the programmer to reason about the code but provides performance challenges. Assignment statements in the MATLAB programming language have different forms, for example:

$$a = \textit{zeros}(10); \tag{1.1}$$

$$b = a; \tag{1.2}$$

$$c = \textit{myfunc}(a, b); \tag{1.3}$$

A naive implementation of the copy semantics for statements 1.1 - 1.3 above would involve making a copy at every assignment statement. Thus, in statement 1.1, the object (a 10 x 10 matrix) allocated by function *zeros* would be copied into variable a. The MATLAB language defines a number of memory allocation functions similar to *zeros*. In statement 1.2, array a would be copied into variable b. In statement 1.3, the arguments a and b in the call to function *myfunc* would be copied into their corresponding parameters of the function; the return value of *myfunc* would also copied into variable c.

With this naive strategy a copy must be generated when: 1) a variable is defined from an existing object; 2) a parameter is passed from one function to another; and 3) a value is returned from a function. Obviously, this is inefficient. A more advanced implementation can detect opportunities to convert copy-by-value to copy-by-reference, and similarly, convert call-by-value to call-by-reference.

The results in Table 1.1 shows that most MATLAB functions have one or more input and/or output parameters. This suggests that in a naive implementation, array copying is potentially a major generator of runtime overhead.

Existing MATLAB systems rely on reference-counting schemes to create copies only when a shared array representation is updated. This reduces array copies, but increases the number of runtime checks.

In addition, reference-counting schemes incur overheads. The approach requires space for storing a reference count for each array object and space for the code that keeps the reference counts updated. Keeping the reference counts updated also generates execution time overhead. Hence, adding a reference-counting scheme to a garbage-collected runtime system will have a negative effect on performance.

Because copying large arrays affects performance, an efficient implementation of array copy semantics in MATLAB is a key optimization for improving the performance of MATLAB programs.

1.3.2 Challenge 2: Function Calls in Loops

The results of the study of MATLAB programs (Table 1.1) reveal that MATLAB programs often contain loops. This is not surprising because MATLAB is an array-based language and loops are typically used to express repetitive operations on arrays. It was also found that a significant proportion of the loops studied have function calls. Based of these results, we can predict that the called functions in those loops are frequently executed. If this happens, it will result in excessive function call overheads. Besides, function calls generally disrupt optimizations, forcing many analyses and transformations to be necessarily conservative. It is also hard to vectorize a loop that contains function calls.

An important optimization technique for eliminating function call and return overheads is function inlining or inline expansion. Inlining optimization involves replacing a call instruction at a call site with the body of the called function. Inlining of call sites that are frequently executed can lead to an improved performance. As an example, consider the following code snippet.

```
1 n = 10000;
2  ...
3 for  i=1:n
4     ...
5    compute(i)  % a  potentially   hot   call
6     ...
7 end
```

The call of function compute in line 5 can prevent loop optimizations such as vectorization. By first inlining compute, however, we increase the opportunity for vectorization and increase the scope for the traditional compiler optimizations. Also, if compute is a straight-line code, the loop computation can be performed on a GPU. The challenge therefore is to dynamically identify and inline the most critical call sites that can lead to a performance improvement.

1.3.3 Challenge 3: Dynamic Function Evaluation (*feval*)

The problem with the dynamic function evaluation via `feval` is related to Challenge 2. An important feature of the MATLAB programming language is its support of higher-order functions through the `feval` construct, which is widely used in many classes of numerical computations, including fitting functions, estimating Ordinary Differential Equations (ODE), machine learning algorithms such as simulated annealing, and general plotting functions. All of these applications share a similar pattern, the main computation function has a function parameter that can accept either a function handle, or a function name as the actual argument. The body of the computation function then repeatedly evaluates the function passed in using `feval`.

However, dynamic function evaluation via `feval` calls within a frequently executed loop can incur high runtime overhead. The `feval` call is often interpreted because the function to be evaluated is generally unknown at the compilation time. This can be very slow. Besides, function evaluation via `feval` built-in prevents important optimizations such as inlining that can increase the scope for other more traditional compiler optimizations such as the common sub-expression elimination (CSE). The challenge therefore is to determine the overhead of `feval` and to develop runtime optimization techniques for reducing or eliminating the overhead, and thus improve performance.

Listing 1.1 – A while loop with an `feval` call.

```
1  while k ≤ maxit
2      k = k + 1;
3      [f,dfdx] = feval(fun,x);   %Returns f( x(k−1) ) and f '( x(k−1) )
4      dx = f/dfdx;
5      x = x − dx;
6      if ( ( abs(f) < feps ) | ( abs(dx) < xeps ) )
7          r = x;
8          return;
9      end
10   end
11 end
```

Listing 1.1 shows a MATLAB code snippet from Gerald Recktenwald's [Rec00a] implementation of Newton's method for finding the root of a polynomial. The code snippet contains a loop with an `feval` call. The first argument to the `feval` call, that is, fun contains the name or a handle to the function that the `feval` call evaluates at run time. An optimization opportunity exists: because fun is a loop constant, then the `feval` call will evaluate the same function at every iteration of the loop. Replacing the `feval` call with a direct call to the function held by variable fun can lead to a significant performance improvement.

In the next section, we provide an overview of the techniques that we have developed to overcome these challenges. We describe the techniques in detail in chapters 3 — 8.

1.4 Solution Overview

The foregoing challenges have been resolved in this thesis by developing suitable optimization techniques as an extension to McJIT, the McVM JIT compiler [CB09, CBHV10]. Three major optimization opportunities that have been identified and addressed are:

1. array copying at assignments and input or output parameter passing;
2. a high number of loops, and a high proportion of loops with function calls;
3. repeated evaluation of a fixed target function by an `feval` call.

1.4.1 Copy Optimization

To harness the first optimization opportunity, we developed an approach that is based on JIT-time static flow analysis. It is a staged static analysis approach that does not require reference counts, thus enabling a garbage-collected virtual machine. It eliminates both unneeded array copies and does not require frequent runtime checks.

The first stage combines two simple, yet fast, intraprocedural forward analyses to eliminate unnecessary copies: the first, *written parameters* analysis determines the parameters that *may* be modified by a function while the second, *copy replacement* analysis determines if all the uses of a copy variable can be replaced by the original so that the copy statement defining the copy can be eliminated.

The second stage is comprised of two analyses that together determine whether a copy should be performed before an array is updated: the first, *necessary copy analysis*, is a forward flow analysis and determines the program points where array copies are required while the second, *copy placement analysis*, is a backward analysis that finds the optimal points to place copies, which also guarantee safe array updates. We return to copy optimization analyses in Chapter 3.

1.4.2 On-Stack-Replacement (OSR) Support

To ensure that a function that is in the middle of an execution can be optimized at a higher optimization level, the dynamic optimizations highlighted below must be supported by an on-stack replacement capability. Unfortunately, however, LLVM does not support on-stack replacement.

So, we implemented OSR for LLVM. We decided to design and develop a modular approach to implementing on-stack replacement in LLVM as part of the research work of this thesis.

Apart from being useful for the techniques developed in the thesis, the modular OSR implementation will allow developers building JIT compilers in LLVM to develop runtime optimizations that can improve the performance of their JIT compilers. We discuss the modular OSR approach in Chapter 4.

1.4.3 Selective Dynamic Inlining of Function Calls in Loops

To exploit the second optimization opportunity, we developed selective inlining of functions at call sites located in frequently executed loop paths. The call sites of interest are annotated at JIT compilation time. They are considered for inlining at run time if the loop iteration count exceeds a pre-set threshold. This optimization is supported by a novel on-stack replacement technique. On-stack replacement is used to continue the execution of the interrupted loop after the inlining. We describe our selective dynamic inlining in detail in Chapter 5.

1.4.4 `feval` Call Specialization

To exploit the third optimization opportunity, we proposed and developed two on-the-fly mechanisms for specialization of `feval` calls. The two approaches aim at replacing `feval` calls with direct calls to the `feval` target function. Thus, eliminating interpreter overhead and allowing an optimization of both the target function and the calling function.

The first approach specializes calls of functions with `feval` using a combination of runtime input argument types and values. The second approach uses on-stack replacement technology, as supported by McVM/McOSR [3]. These two specialization approaches are described in detail in chapters 6 – 8.

1.5 Research Contributions

We have designed and developed several techniques that can be used to improve the performance of virtual machines and JIT compilers for the MATLAB programming language. Our techniques can also be used to improve the implementations of other similar dynamic languages. To the best of our knowledge, we are not aware of similar work for the MATLAB language. We highlight our main contributions below.

3. www.sable.mcgill.ca/mclab/mcosr.

1.5.1 Copy Optimization in McVM

Copy elimination optimization: We designed and implemented a novel copy optimization technique, supported by our four new flow analyses, to efficiently implement array copy semantics in a MATLAB JIT Compiler. Our approach is suitable for implementing array copy semantics in a garbage-collected virtual machine.

Experimental measurements of overheads: We conducted experiments to demonstrate the behaviour of reference-counting approaches and to measure the overhead associated with dynamic checks in a reference-counting approach.

Experimental measurements of impact: We showed that for our benchmark set, our JIT compilation-time static approach finds the needed number of copies, without introducing any dynamic checks.

1.5.2 Modular On-Stack Replacement in LLVM

Modular OSR in LLVM: We have designed and implemented OSR for LLVM. Our approach provides a clean API for JIT compiler writers using LLVM and clean implementation of that API, which integrates seamlessly with the standard LLVM distribution and that should be useful for a wide variety of applications of OSR.

Integrating OSR with inlining in LLVM: We show how we handle the case where the LLVM inliner inlines a function that contains OSR points.

Experimental measurements of overheads: We have performed a variety of measurements on a set of MATLAB benchmarks. We have measured the overheads of OSR. This shows that the overheads are usually acceptable.

1.5.3 Selective Dynamic Inlining

Using OSR in McJIT for selective dynamic inlining: In order to demonstrate the effectiveness of our OSR module, we have implemented an OSR-based dynamic inliner that will inline function calls within dynamically hot loop bodies. This has been completely implemented in McVM/McJIT. We also designed two OSR point placement strategies for inserting an OSR point into a loop within a loop nest.

Experimental measurements of benefits: We have performed a variety of measurements on a set MATLAB benchmarks. We have measured the benefits of selective dynamic inlining. This shows dynamic inlining can result in performance improvements.

1.5.4 Dynamic Function Dispatch via the MATLAB `feval`

Measuring the cost of `feval`: We evaluated the overheads of `feval` and show significant overheads for calls via `feval` for important classes of benchmarks.

OSR-based specialization of `feval`: We developed a general technique to detect and instrument important `feval` sites with OSR points, and we designed an OSR-based transformation which can be done at the LLVM IR-level, without requiring access to the generated assembly code. We also designed appropriate JIT-time tests to optimize the guards required to determine if the specialized call could be made or if the general backup path should be taken.

JIT value-based specialization: We designed an extension to the McVM JIT specialization mechanism. Previously specialization was performed based only on the dynamic **types** of function arguments. In the new approach, we also specialize on the **value** of a function argument, for the case where that argument is used as the first argument to a call to `feval` inside the body of the function to be compiled.

Implementation in McVM/McOSR: We implemented the two approaches in McVM. Our implementation is open source.

Experimental results: We evaluated the OSR-based specialization and JIT value-based specialization approaches on a set of benchmarks. We also compared the performance of the OSR-based specialization approach with that of the JIT value-based specialization approach (Chapter 7).

1.6 The Organization of the Thesis

This thesis is divided into five parts. The first part consists of Chapter 2, where we provide the necessary background to the research work described later in the thesis.

The second part consists of Chapter 3. There, we describe our approach to an efficient implementation of array-copy semantics in MATLAB. We also discuss our experimental results that show significant overhead for dynamic checks in reference-counting-based implementations, and the experimental results that demonstrate the effectiveness of our approach.

The third part is comprised of Chapter 4 and Chapter 5. In Chapter 4, we describe our implementation of OSR in LLVM. In Chapter 5, we describe our implementation of selective dynamic inlining that is based on the OSR approach. We then present the results of our experiments that measure the overhead of OSR over a set of benchmarks. We also discuss the experimental results that show the benefits of the OSR-supported selective dynamic inlining.

The fourth part is comprised of Chapter 6, Chapter 7, and Chapter 8. In Chapter 6, we motivate the need for an `feval` call specialization. In particular, we describe our experimental results that show significant overheads for `feval` call implementations in several interpreters and JIT compilers for the MATLAB programming language. In Chapter 7, we describe our first specialization approach — the OSR-based `feval` specialization approach. In Chapter 8, we describe the second approach — the JIT value-based specialization approach.

The last part consists of Chapter 9 and Chapter 10. We review some related work in Chapter 9. We conclude the thesis and highlight the direction for future work in Chapter 10.

Chapter 2
Background: MATLAB, McVM and LLVM Compiler Framework

The research work presented in this thesis is based on several existing systems. MATLAB® system is a proprietary implementation of the MATLAB programming language by MathWorks®. [1] Throughout the thesis, the term MATLAB may refer to the MathWorks' implementation of the MATLAB programming language or the MATLAB programming language. It will be clear from the context which meaning is being referred to. The research was conducted within the McLAB virtual machine, McVM [CB09, CBHV10], which is supported by the LLVM compiler framework [LA04].

To aid the understanding of the work described later in the thesis, we briefly introduce the MATLAB programming language. We then describe McVM and its JIT compiler, McJIT. We conclude the chapter with an introduction to the LLVM compiler framework, with a special focus on the JIT compiler toolkit of the framework.

2.1 MATLAB

The MATLAB system includes an interactive computing environment. A MATLAB user types a command and the MATLAB system evaluates the command. Users can also

1. http://www.mathworks.com/products/pfo/.

invoke a MATLAB file from the interactive environment. A file containing valid MATLAB code is called an M-file. MATLAB accepts two kinds of M-files: *scripts* and *functions*.

A script is a sequence of MATLAB statements or commands; it does not accept any arguments and does not return any values. A script operates on data in the MATLAB workspace. For the purpose of the discussions in this thesis, we shall concentrate on MATLAB functions and will not discuss MATLAB scripts further. More information on MATLAB scripts can be found in numerous MATLAB books, including the Matlab 7 Getting Started Guide [Mat09a].

A MATLAB function can accept zero or more arguments and can return zero or more values. Variables defined in a function are internal to the function.

MATLAB is a dynamically typed language. This means that the runtime value of a variable determines the type of the variable. Listing 2.1 shows a MATLAB function that computes the product of two matrices.

Listing 2.1 – A matrix multiplication MATLAB function.

```
1  function c = matrixmul(a, b)
2    [m, n] = size(a);
3    [n1, p] = size(b);
4    if (n ~= n1)
5      error('Non conforming matrices');
6    end
7    c = zeros(m, p);
8    for i=1:m
9      for j=1:p
10       for k=1:n
11         c(i,j) = c(i,j) + a(i,k) * b(k,j);
12       end
13     end
14   end
15 end
```

Listing 2.2 – A matrix multiplication driver.

```
1 function matrixmul_driver()
2   N = 10;
3   a = rand(N, N);
4   b = rand(N, N);
5   c = matrixmul(a, b);
6   disp(c);
7 end
```

As shown in Listing 2.1, a function in MATLAB begins with the keyword **function** and ends with another keyword **end**.[2] MATLAB considers an array access as a mapping from the index type to the array element type. Thus, MATLAB uses identical syntax for array accesses and function calls. As will be shown later in the thesis (Section 3.6), using the same syntax for both array accesses and function calls can increase compilation difficulties.

Listing 2.3 – A matrix multiplication driver using MATLAB "*" operator.

```
1 function simple_matrixmul_driver()
2   N = 10;
3   a = rand(N, N);
4   b = rand(N, N);
5   c = a * b;
6   disp(c);
7 end
```

As mentioned earlier, MATLAB is an array-based language designed for sophisticated vector and matrix operations. Therefore, function matrixmul_driver in Listing 2.2 and simple_matrixmul_driver in Listing 2.3 are semantically equivalent MATLAB programs. Function **rand** is a memory-allocating MATLAB built-in function. The standard MATLAB library defines several thousand MATLAB built-in functions.

Function matrixmul shown in Listing 2.1 accepts two parameters and returns a value. MATLAB uses call-by-value semantics for passing parameters. Thus, MATLAB functions do not have side-effects due to writing parameters and local variables.

2. In certain cases, the keyword **end** at the end of a function may be omitted.

Function Handles It is possible to create a handle to a MATLAB function. According to the MATLAB 7 Getting Started Guide [Mat09a], a function handle is typically passed as an argument to other functions that can evaluate or execute the function referenced by the function handle variable. The following code snippet creates a function handle to built-in function *tan*.

```
fh = @tan;
```

A MATLAB function can be called using its name or via a function handle. For example, `fh(60);` calls the MATLAB built-in function **tan** passing 60 to it as an argument.

2.2 The McLab Virtual Machine

McVM is a virtual machine for the MATLAB programming language. It is a key component of the McLAB framework [mcl]. Figure 2.1 shows the main components of the McLAB project. The McLAB framework is comprised of an extensible front-end, a high-level analysis and transformation engine and five backends. Currently there is support for the core MATLAB language and also a complete extension supporting ASPECTMATLAB [ADDH10]. The front-end and the extensions are built using Metalexer [CH11], and JastAdd [EH07]. There are five backends: McFor, a FORTRAN code generator [Li09]; Mc2For, a new FORTRAN code generator [mc213]; MiX10, an X10 [KH13] code generator; a MATLAB generator (to use McLAB as a source-to-source compiler); and McVM, a virtual machine that includes a simple interpreter and a sophisticated type-specialization-based JIT compiler, named McJIT, which generates LLVM [LA04] code.

In Figure 2.2, we show the main components of McVM. McVM has a JIT compiler and an interpreter. As shown in the figure, the VM is supported by a number of analyses, including, *live variable*, *array bounds check elimination*, *type inference* and *copy elimination* analyses. The copy analyses (Chapter 3), OSR library (Chapter 4), dynamic inliner (Chapter 5), `feval` optimization logic (Chapter 6, Chapter 7, and Chapter 8) are parts of the research contributions of this thesis.

McVM is also supported by Boehm garbage collector [BS07], and several numerical libraries [ABB+99,WPD01]. It supports most MATLAB data types, including logical arrays,

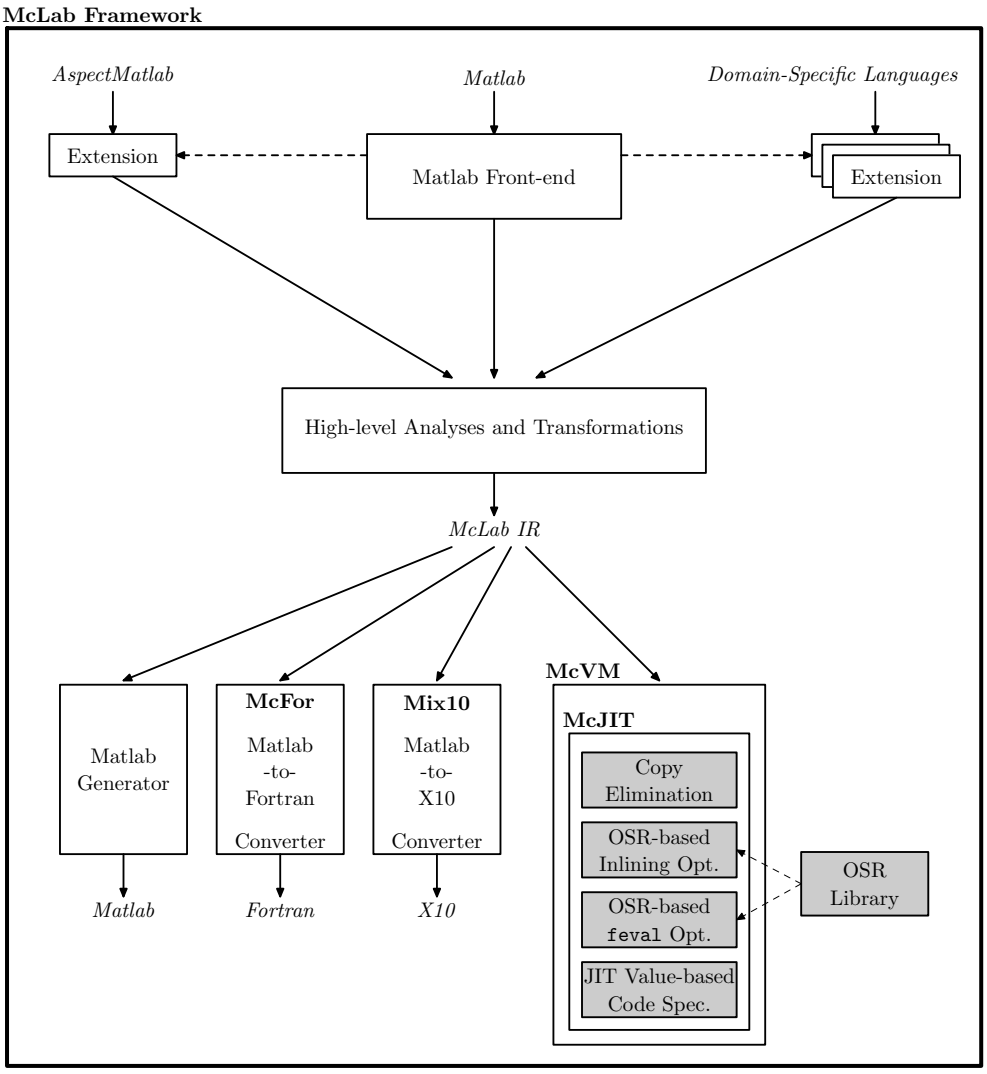


Figure 2.1 – Overview of the McLAB project (shaded boxes are contributions of this thesis).

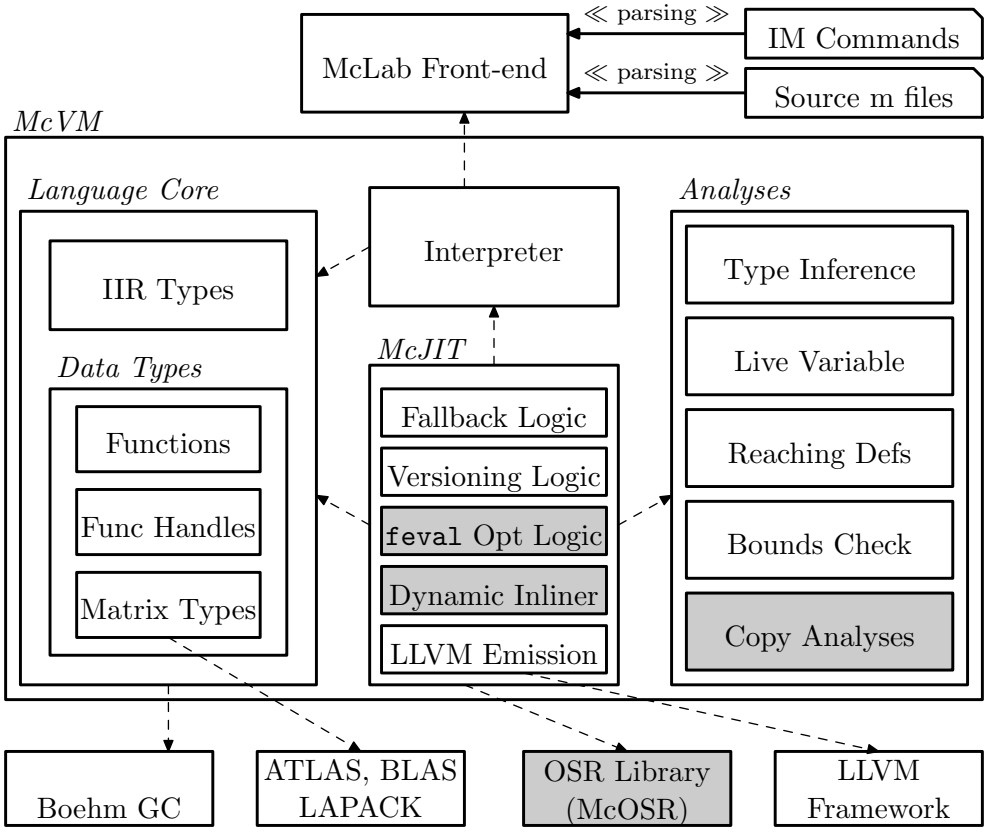


Figure 2.2 – The main components of McVM (adapted from [CB09]). The shaded components are parts of the research work presented in this thesis.

double-precision floating points, double-precision complex-number matrices, cell arrays and function handles.

2.2.1 Type Inference and Specialization

McVM is supported by a type-inference engine. It is a key performance driver for the McVM JIT compiler. The type information provided by the inference engine is used by McJIT for function specialization.

The type inference is a forward analysis that propagates for each variable, the set of possible types through every branch of a function. Variables can have different types at different points in a function.

The type inference assumes that for each input argument, the set of possible types are known. Given the initial types, it infers, at each program point, the set of possible types for a variable. The analysis may generate different results for each function depending on the input arguments passed in to the function during a call.

McJIT specializes code based on the function argument types that occur at run time. When a function is called the VM checks to see if it already has a compiled version corresponding to the current argument types. If it does not, it applies a sequence of analyses including the live variable analysis and type inference. Eventually, it generates LLVM code for the current version. Next, we discuss how McVM executes a user function.

2.2.2 Running a Function

McVM uses the McLAB front-end to parse the input MATLAB commands and source files (*mfiles*). The McLAB front-end sends its output to McVM as an XML file or string. McVM then creates an abstract syntax tree (AST) for the source code from the XML file or code string.

In Figure 2.3, we illustrate how McVM, with its JIT compiler enabled, executes a user-defined function. When a function is called with arguments of some data type, as shown in the figure, the VM checks whether a compiled code version that matches the argument types exists in the code cache. If a matching version is found, it directly executes the code.

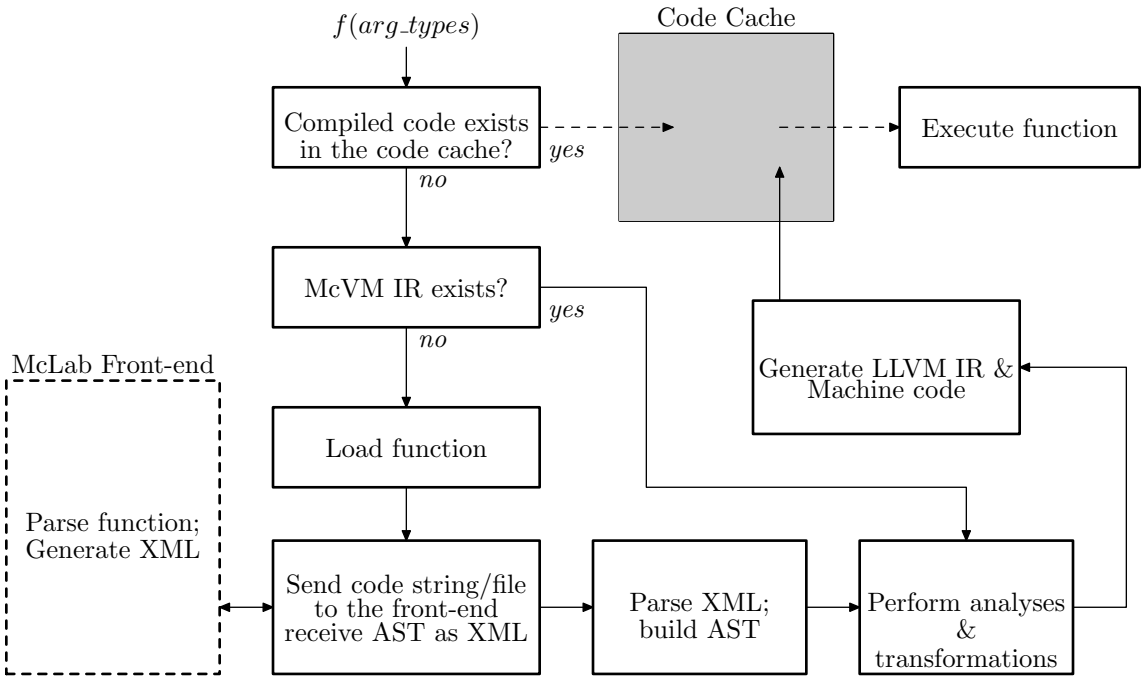


Figure 2.3 – Running a function in McVM.

Otherwise, it checks whether a McVM AST has been created for the function and proceeds to perform a series of analyses and transformations on the IR (McVM AST). Then it produces LLVM code, which is then passed to the LLVM code generator to produce the machine code for the function. The address of the generated machine code is stored in the code cache.

If McVM IR has not been created for the function, the source code is loaded and passed to the McLAB front-end for lexical analysis and parsing. McVM then generates McVM IR for the source code and proceeds to the other stages of the code compilation shown in Figure 2.3.

2.2.3 McJIT-Interpreter Interaction

McJIT occasionally generates calls to the interpreter to compute certain complicated expressions that it is unable to handle or that the JIT compiler does not currently support. The interaction between the compiler and interpreter is often facilitated through a symbol

look-up environment. A symbol environment is a table that associates a value to a symbol. It is used to bind a value to a variable, and to look-up the value of a variable at run time.

The code setting up a symbol look-up environment for a function is generated lazily on a need basis. During the code generation for a function, the first time McJIT generates an LLVM instruction that requires a symbol environment, it generates the symbol environment set-up code at the function's prologue. The set-up code initializes the environment for subsequent look-ups and bindings of values to variables. This can be a major source of overhead. In Section 5.2, we show how to minimize the overhead of this symbol environment set-up code.

2.3 The LLVM Compiler Framework

LLVM is an open source compiler infrastructure that can be used to build compilers for static languages and JIT compilers for virtual machines. LLVM is designed as a set of libraries with well-defined interfaces. It supports a well-defined low-level intermediate code representation known as the LLVM IR, as well as supporting a large number of optimizations and code generators for a variety of architectures.

The compiler infrastructure is being used in many research projects and in some production systems. LLVM has been used to implement statically compiled languages such as C/C++ and dynamic languages such as MATLAB, Ruby, and JavaScript. Recently, an OpenCL GPU programming language implementation was added to LLVM. Apple's OpenGL stack and Adobe's After effect also use LLVM [BW11].

This section introduces the LLVM compiler framework from the perspective of a JIT compiler developer.

2.3.1 The Three-Phase Design of LLVM

Figure 2.4 shows the three-phase design of LLVM. The first phase of the design includes the front-ends and the last phase of the design includes the back-ends. Connecting the front-ends to the back-ends is the LLVM Optimizer.

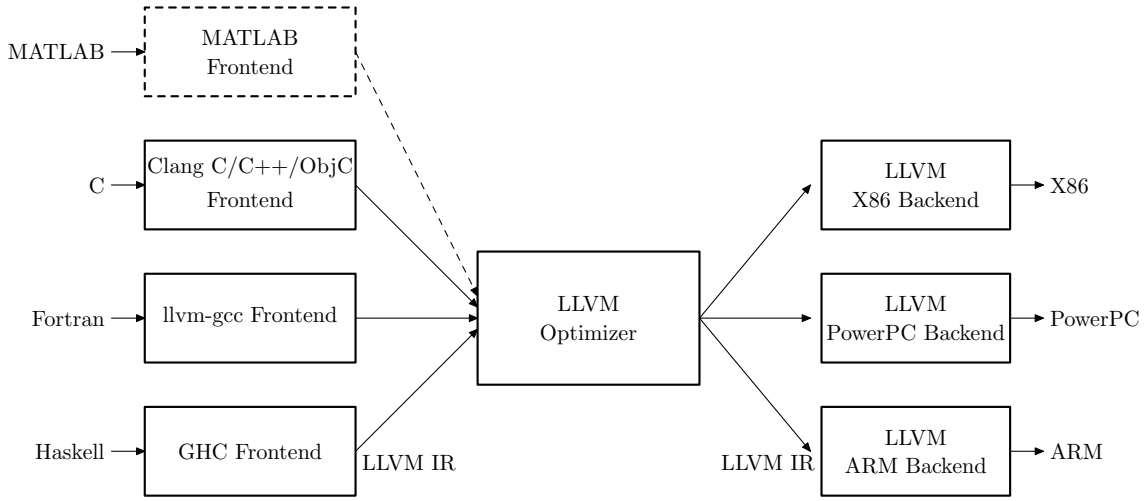


Figure 2.4 – Three-phase Design of LLVM (adapted from *The Architecture of Open Source* [BW11]). To implement the MATLAB language in LLVM, a MATLAB front-end must be implemented.

A front-end for a new language produces code in LLVM IR. LLVM is strongly typed. The IR instructions are in three-address form: they accept some typed inputs and produce results in new virtual registers. The IR also supports labels. The LLVM IR is in static single assignment (SSA) form [AWZ88, RWZ88, CFR+89, BBH+13]. SSA form IR simplifies many optimizations, including constant propagation, global value numbering and dead-code elimination. We review SSA form in Section 2.3.2.

The optimizer performs target-independent analyses and transformations on the LLVM IR. The output from the optimizer forms the input to the back-ends. LLVM provides back-ends for common architectures, including x86, IBM PowerPC, and ARM. A developer can add back-ends for new architectures.

As can be observed from Figure 2.4, LLVM uses a common optimizer. Thus, implementations of multiple programming languages can share a single back-end. To implement a new language, a developer needs only to implement a front-end for the new language and use the existing back-ends. As illustrated in Figure 2.4, a developer implementing a JIT compiler in LLVM for the MATLAB language only needs to implement the front-end (the box made of dashed lines in Figure 2.4). The implementation can use the existing LLVM

back-ends. Without this design, implementing N languages for M architectures would require $N * M$ back-ends — a really daunting task.

2.3.2 Static Single Assignment (SSA) Form

The LLVM IR is in static single-assignment form. SSA form is a code transformation where program variables satisfy the property that there is only one assignment to them in the program. Because we shall be discussing several LLVM IR-transformations in Chapter 4, to simplify later discussions on LLVM IR-level transformations, we review the SSA form here. First, a review of the dominance relation [Tar74] between nodes in a control flow graph is presented.

dominator: A node X dominates a node Y, if every execution path from **entry** to Y goes through X. We write X *dom* Y if a node X dominates a node Y.

postdominator: A node Y postdominates a node X if every execution path from X to **exit** goes through Y.

strict dominance A node X strictly dominates a node Y if X dominates Y and $X \neq Y$. We write X *sdom* Y if a node X strictly dominates a node Y.

immediate dominator: An immediate dominator of a node Y, denoted by *idom*(Y), is a node X such that X is the closest strict dominator of Y on any path from **entry** to Y. Every node (except the entry node) has exactly one immediate dominator.

join point: A join point is a node with more than one incoming edge.

Consider the MATLAB code in Listing 2.4.

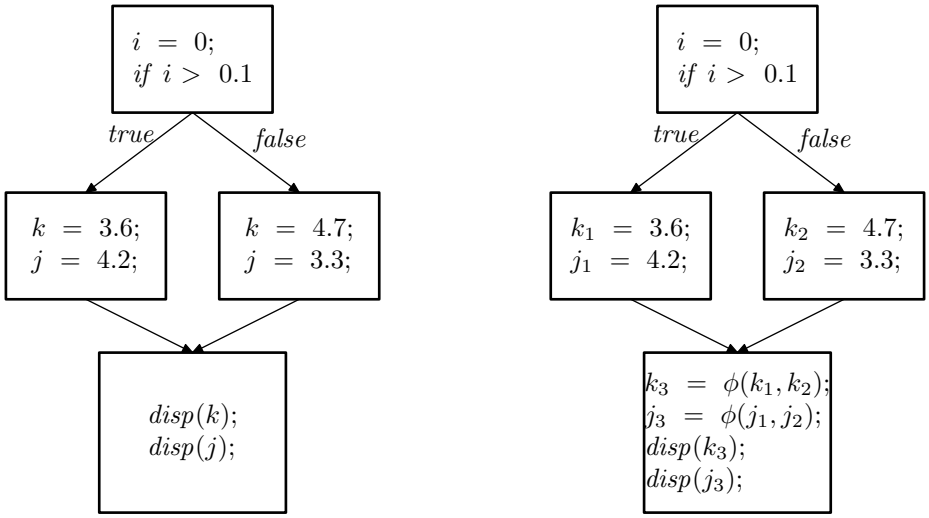


Figure 2.5 – A CFG for function test is shown in (a); an equivalent CFG for the function in SSA form is shown in (b).

Listing 2.4 – A MATLAB function with an *if-else* statement.

```
1  function test ()
2    i = 0.0
3    if i > 0.1
4      k = 3.6;
5      j = 4.2;
6    else
7      k = 4.7;
8      j = 3.3;
9    end
10   disp(k);
11   disp(j);
12 end
```

A corresponding control flow graph (CFG) is given in Figure 2.5 (a). Converting code in an intermediate representation into an SSA form involves renaming variables and inserting pseudo assignments named *phi* functions at join points. The CFG for function test in SSA form is shown in Figure 2.5 (b).

As shown in the figure, *phi* nodes have been inserted to merge multiple definitions of a variable that reach the join point (*BB4*).

Several algorithms [AWZ88, RWZ88, CFR+89, BBH+13] exist to convert code in an intermediate representation into an SSA form. Minimal SSA form for a function inserts the minimum number of *phi* functions. A function can be converted into minimal SSA form by computing the *dominance frontiers* [CFR+89] of all nodes.

The *dominance frontier* of a node X denoted as $DF(X)$ is the set of nodes Y such that X dominates a predecessor of Y but does not strictly dominate Y. Formally,

$$DF(X) = \{Y | (\exists P \in Pred(Y))(X\ dom\ P \wedge X\ !sdom\ Y)\}$$

For a set of nodes S of the control flow graph, the dominance frontier of S is defined as

$$DF(S) = \bigcup_{X \in S} DF(X)$$

and the *iterated dominance frontier* of S

$$DF^{+} = \lim_{i \to \infty} DF^{i}(S)$$

where

$$DF^{1}(S) = DF(S);$$
$$DF^{i+1}(S) = DF(S \cup DF^{i})$$

The set $J(S)$ of join nodes is defined as the set of all nodes Z such that there are two CFG paths that start at two distinct nodes in S and have Z as the first node in common.

The *iterated* join $J^{+}(S)$ is defined as

$$J^{+} = \lim_{i \to \infty} J^{i}(S)$$

where

$$J^1 = J(S);$$
$$J^{i+1} = J(S \cup J^i)$$

Cytron et al. [CFR+89] show that if S is the set of assignment nodes for a variable V, the iterated join of S is equivalent to the iterated dominance frontier of S. Thus, $DF^+(S)$ is exactly the set of nodes that need ϕ nodes for variable V.

We now present examples of code in LLVM IR.

2.3.3 LLVM IR: Examples

In this section, we introduce LLVM IR. Listing 2.5 shows a MATLAB function that returns the sum of its two parameters. A corresponding LLVM IR for the MATLAB function is shown in Listing 2.6.

Listing 2.5 – A simple MATLAB function.

```
1 function r = addDoubles(arg1, arg2)
2   r = arg1 + arg2;
3 end
```

The code uses instruction fadd to add the values of **%arg1** and **%arg2**. The operands of fadd are floating point values.

Listing 2.6 – LLVM IR for *addDoubles*.

```
1 define double addDoubles(double %arg1, double %arg2) {
2   %tmp = fadd double %arg1, %arg2
3   return double %tmp
4 }
```

To give a hint of the optimizing power of LLVM, we show two semantically equivalent implementations for the MATLAB function in Listing 2.4. The first is a naive implementation while the second folds memory operations (load/ store instructions) into ϕ nodes to produce a more efficient implementation of test .

Listing 2.7 – A naive implementation of test (Listing 2.4) in LLVM IR.

```
1  define void @test() {
2  entry:
3    %i = alloca double
4    %j = alloca double
5    %k = alloca double
6    store double 0.000000e+00, double* %i
7    %iVal = load double* %i
8    %ifCond = fcmp ogt double %iVal, 1.000000e-01
9    br i1 %ifCond, label %then, label %else
10
11 then:                                             ; preds = %entry
12   store double 3.600000e+00, double* %k
13   store double 4.200000e+00, double* %j
14   br label %exit
15
16 else:                                             ; preds = %entry
17   store double 4.700000e+00, double* %k
18   store double 3.300000e+00, double* %j
19   br label %exit
20
21 exit:
   ; preds = %else, %then
22   %nK = load double* %k
23   %nJ = load double* %j
24   %0 = call i64 @dispDB(double %nK)
25   %1 = call i64 @dispDB(double %nJ)
26   ret void
27 }
```

In Listing 2.8, all the memory accesses in Listing 2.7 have been converted to register reads/writes. The LLVM instruction set allows an infinite set of virtual registers.

Listing 2.8 – A more optimized implementation of *test* (Listing 2.4) in LLVM IR.

```
1  define void @test() {
2  entry:
3    %ifCond = fcmp ogt double 0.000000e+00, 1.000000e-01
4    br i1 %ifCond, label %then, label %else
5
6  then:                                             ; preds = %entry
7    br label %exit
8
9  else:                                             ; preds = %entry
10   br label %exit
11
12 exit:
   ; preds = %else, %then
13   %j.0 = phi double [ 4.200000e+00, %then ], [ 3.300000e+00, %else ]
14   %k.0 = phi double [ 3.600000e+00, %then ], [ 4.700000e+00, %else ]
15   %0 = call i64 @dispDB(double %k.0)
16   %1 = call i64 @dispDB(double %j.0)
17   ret void
18 }
```

2.3.4 LLVM Transformation and Optimization Pass

LLVM provides a framework for transforming and optimizing code in LLVM IR. Transformations and optimizations are written as passes. An LLVM pass is a subclass of Pass or its several, similarly named, derived classes, including, BasicBlockPass for basic block-level transformations; FunctionPass for function-level transformations; and ModulePass for module-level transformations. We shall illustrate how to write an LLVM pass with a function-level pass.

Suppose we want to count the number of call instructions in a function. One can write a function-level pass that scans the instructions in the function and updates a counter when it finds a call instruction.

Listing 2.9 – An example of a function pass.

```
1  namespace {
2    using namespace llvm;
3    // counts the number of function calls in a function
4    class CallCountPass : public FunctionPass {
5    public:
6    CallCountPass() : FunctionPass(ID), callCount(0) {}
7
8      unsigned getCallCount() const { return callCount;}
9
10     virtual bool runOnFunction(Function& F) {
11       countCalls(F); return false;
12     }
13
14     virtual const char* getPassName() const {
15       return "Call Counter Pass";
16     }
17     static char ID;
18   private:
19     // counts the number of call instructions in a Function
20     void countCalls(Function& F) {
21       for(Function::const_iterator FI = F.begin(),
22           FE = F.end(); FI != FE; ++FI) {
23         const BasicBlock& BB = *FI;
24         for(BasicBlock::const_iterator BI = BB.begin(),
25             BE = BB.end(); BI != BE; ++BI) {
26           const Instruction * I = &*BI;
27           if (isa<CallInst>(I)) ++callCount;
28         }}}
29     unsigned callCount;
30   };
31
32   FunctionPass* createCallCountPass () {
33     return new CallCountPass(); }
34   char CallCountPass::ID = 0;
35 }
```

Listing 2.9 shows a function pass that counts the number of calls in a function in LLVM IR. Class CountCallPass is derived from the standard FunctionPass, so it is a function-level pass. It operates on a function via method runOnFunction whose input is a valid function in LLVM IR. Method runOnFunction returns **false** to indicate that it does not modify the CFG. If a pass modifies the input LLVM IR, it must return **true**.

As shown in Listing 2.9, class CountCallPass defines a private method named countCalls. The method is called by runOnFunction. In lines 17 – 24, countCalls traverses the CFG and increments a counter in line 24 if the current instruction is a call instruction. After scanning all the basic blocks in the function, data member callCount will contain the count of all the call instructions in the analyzed function.

LLVM provides a variety of pass managers to organize and schedule passes to be run on input code in LLVM IR. FunctionPassManager can be used to schedule passes to be run on functions in LLVM IR. For instance, the following code snippet creates a function pass manager and adds some optimization/transformation passes to the pass manager.

```
...
FunctionPassManager FPM(module);
FPM.add(createCountCallPass ());
FPM.add(createConstantPropagationPass ());
FPM.add(llvm::createPromoteMemoryToRegisterPass());
FPM.add(createGVNPass());
FPM.add(createEarlyCSEPass());
...
```

In the code snippet, five different passes were submitted to the pass manager (FPM). The user runs the passes in the order of their creation by calling method run of FunctionPassManager and passing the input function such as F in the following code snippet. A user can also specify dependencies between passes. This can change the order in which passes are run on an input LLVM IR function.

```
...
FPM.run(*F);
...
```

The call to method run will cause all the four passes to be run on function F.

2.3.5 LLVM JIT Execution Engine

LLVM provides several execution engines that can be used to execute or interpret LLVM IR. The JIT execution engine allows runtime code generation and is suitable for

building JIT compilers for dynamic languages. The LLVM framework also has an LLVM IR interpreter.

To build a JIT compiler for a programming language, a user needs to create a JIT execution engine. Method createJIT of the class ExecutionEngine can be used to create a JIT execution engine. A user can also use the class EngineBuilder to create an execution engine. The following code snippet shows how to use EngineBuilder to create a suitable execution engine.

Listing 2.10 – Creating a JIT execution engine.

```
1 using namespace llvm;
2  ...
3 EngineBuilder EB(module);
4 EB.setOptLevel(CodeGenOpt::Default);
5 EB.setEngineKind(EngineKind::Kind::JIT);
6 ExecutionEngine* jitEE = EB.create();
7  ...
```

In the code snippet shown in Listing 2.10, the statement in line 2 creates an engine builder. In line 3, the code generation optimization level is set to its default optimization level. Line 4 sets the execution engine kind to JIT and the statement in line 5 creates a JIT execution engine using the settings from the engine builder object (EB).

2.4 Summary

In this section, we introduced the most relevant systems used for the work presented in the thesis, which is on runtime optimization techniques for implementing the MATLAB programming language.

The chapter began with an introduction to them MATLAB programming language. We later introduced McVM— an open-source implementation of MATLAB. McVM is based on the LLVM compiler framework. We reviewed LLVM at the end of the chapter.

LLVM supports JIT compilation and execution via its JIT execution engine. Although LLVM provides support for recompilation of functions, it does not support on-the-fly optimizations. In other words, a running function cannot be transformed or optimized until all its instructions have been executed.

In chapters 3 – 8, we present the research work of this thesis, corresponding to the shaded boxes in Figure 2.1.

Chapter 3
Copy Optimization in MATLAB

In the previous chapter, we introduced the MATLAB programming language and its implementation in McVM. The problem addressed in this chapter is the efficient compilation of the array copy semantics defined by the MATLAB language. The basic semantics and types in MATLAB are very simple. Every variable is assumed to be an array (scalars are defined as 1x1 arrays) and copy semantics is used for assignments of one array to another array, parameter passing and for returning values from a function. Thus a statement of the form `a = b` semantically means that a copy of `b` is made and that copy is assigned to `a`. Similarly, for a call of the form `a = foo(c)`, a copy of `c` is made and assigned to the parameter of the function `foo`, and the return value of `foo` is copied to `a`. Naive implementations take exactly this approach.

In the current implementations of MATLAB, however, the copy semantics is implemented lazily using a reference-count approach. The copies are not made at the time of the assignment, rather an array is shared until an update to one of the shared arrays occurs. At update time (for example a statement of the form `b(i) = x`), if the array being updated (in this case `b`) is shared, a copy is generated, and then the update is performed on that copy. We have verified that this is the approach that Octave open-source system [gnu12] takes (by examining and instrumenting the source code). We believe that this approach (or a small variation) is what the Mathworks' closed-source implementation does based on the user-level documentation [Mat09b, p. 9-2].

Although the reference-counting approach reduces unneeded copies at run time, it introduces many redundant checks, requires space for the reference counts, and requires extra code to update the reference counts. This is clearly costly in a garbage-collected VM, such as the recently developed McVM, a type-specializing JIT [CBHV10, CB09]. Furthermore, the reference-counting approach may generate a redundant copy during an update of a shared array via a variable if all the other variables that reference the array are dead variables.

Thus, our challenge was to develop a static analysis approach, suitable for a JIT compiler that could determine which copies were required, without requiring reference counts and without the expense of dynamic checks. Since we are in the context of a JIT compiler, we developed a staged approach. The first phase applies very simple and inexpensive analyses to determine the obvious cases where copies can be avoided. The second phase tackles the harder cases, using a pair of more sophisticated static analyses: a forward analysis to locate all places where an array update requires a copy (*necessary copy analysis)* and then a backward analysis that moves the copies to the best location and which may eliminate redundant copies (*copy placement analysis*). We have implemented our analyses in the McJIT compiler as structured flow analyses on the low-level AST intermediate representation used by McJIT.

To demonstrate the applicability of our approach, we have performed several experiments to: (1) demonstrate the behaviour of the reference-counting approaches, (2) to measure the overhead associated with the dynamic checks in the reference-counting approach, and (3) demonstrate the effectiveness of our static analysis approach. Our results show that actual needed copies are infrequent even though the number of dynamic checks can be quite large. We also show that these redundant checks do contribute significant overheads. Finally, we show that for our benchmark set, our static approach finds the needed number of copies, without introducing any dynamic checks.

In this chapter, we first describe how the work presented here fits into McVM project discussed in the Chapter 2. Then, we describe the simple first-stage analyses followed by a description of the second-stage forward and backward analyses, with examples. We conclude the chapter with a discussion of our experimental results.

3.1 Background

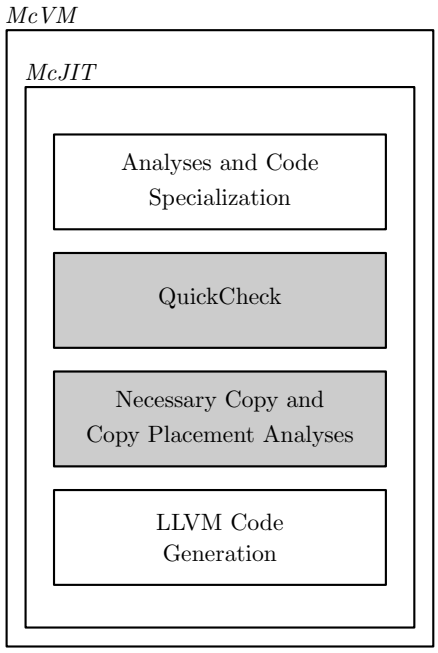


Figure 3.1 – A simplified overview of McJIT (shaded boxes correspond to the analyses presented in this chapter).

The techniques presented in this chapter have been implemented in McJIT (described in Section 2.2), a JIT compiler for MATLAB. In Chapter 2, we highlighted how McJIT specializes code based on the function argument types that occur at run time. When generating code McJIT assumes reference semantics, and not copy semantics, for assignments between arrays and parameter passing. That is, arrays are dealt with as pointers and only the pointers are copied. Clearly this does not match the copy semantics specified for MATLAB and thus the need for the two shaded boxes in Figure 3.1 in order to determine where copies are required and the best location for the copies. These two analysis stages are the core of the techniques presented in this chapter. It is also important to note that the specialization and type inference in McJIT means that variables that certainly have scalar types will be stored in LLVM registers and thus the copy analyses only need to consider the remaining variables.

In the next section, we introduce the first stage of our approach, which is the *QuickCheck*. Following that we introduce the second stage — the *necessary copy* and *copy placement* analyses.

3.2 Quick Check

The *QuickCheck* phase (*QC*) is a combination of two simple and fast analyses. The first, *written parameters analysis*, is a forward analysis which determines the parameters that *may* be modified by a function. The intuition is that during a call of the function, the arguments passed to it from the caller need to be copied to the corresponding formal parameters of the function only if the function may modify the parameters. Read-only arguments do not need to be copied. For example,

```
function foo(arg1, arg2)
    disp(arg1);
    arg2(1) = 1;
end
```

in function *foo* above, only *arg2* of the function needs to be copied. There is no need to copy *arg1* since it is only read and not modified by *foo*.

The analysis computes a set of pairs, where each pair represents a parameter and the assignment statement that last defines the parameter. For example, the entry (p_1, d_1) indicates that the last definition point for parameter p_1 is statement d_1. The analysis begins with a set of initial definition pairs, one pair for each parameter declaration. The analysis also builds a *copy list*, a list of parameters which must be copied, which is initialized to the empty list. The analysis is a forward flow analysis, using union as the merge operator. The key flow equations are for assignment statements of two forms:

***p = rhs*:** If the left-hand side (*lhs*) of the statement is a parameter *p*, then this statement is redefining *p*, so all other definitions of *p* are killed and this new definition of *p* is generated. Note that according to the MATLAB copy semantics, such a statement is not creating an alias between *p* and *rhs*, but rather *p* is a new copy; subsequent writes to *p* will write to this new copy.

***p(i) = rhs*:** If the *lhs* is an array index expression (i.e., the assignment statement is writing to an element of *p*), and the array symbol *p* is a parameter, it checks if the initial definition of the parameter reaches the current assignment statement and if so, it inserts the parameter into the copy list.

At the end of the analysis, the copy list contains all the parameters that must be copied before executing the body of the function.

The second analysis is *copy replacement*, a standard sort of copy propagation/elimination algorithm that is similar to the approach used by an APL compiler [Wei85]. It determines when a copy variable can be replaced by the original variable (copy propagation). If all the uses of the copy variable can be replaced by the original variable then the copy statement defining the copy can be removed after replacing all the uses of the copy with the original (copy elimination).

To illustrate this point, consider the following equivalent code snippets. Variable b in statement 3 of Box 1

Box 1:	
1:	a = rand(15000);
2:	b = a;
3:	c = 2*b

Box 2:	
1:	a = rand(15000);
2:	b = a;
3:	c = 2*a;

can be replaced with a as done in Box 2; since b is not referenced after statement 3, statement 2 in Box 2 can be removed by the dead-code optimizer.

The copy replacement analysis computes a set of pairs of variables by examining assignment statements of the form *b = a*. A pair represents the *lhs* and *rhs* of an assignment statement, and indicates that if a successor of the statement *uses* the first member of the pair then the variable used could be replaced with the second member of the pair. For example, if the pair, (b, a) reaches the statement *c = 2*b* then b could be replaced with a in the statement.

Like the *written parameters* analysis, it is a forward flow analysis. However, in this case the merge function is intersection. The key flow equations for copy replacement analysis are:

b* = *a if both the *lhs* and the *rhs* are variables, a new pair of variables, that is, (b, a) is generated at the statement.

lhs* = *rhs if *lhs* is a member of a pair that reaches the statement, such pairs are killed at the statement. This is because the statement is redefining *lhs* and its new value may no longer match that of the other member of the pairs.

At the end of the analysis, the analyzed function is transformed using the result of the analysis.

If the analysed function does not return an array and all the remaining copy statements have been made redundant by the QC transformation, then there is no need to apply a more sophisticated analysis. If copies do remain, however, then phase 2 is applied, as outlined in the next two sections.

3.3 Necessary Copy Analysis

The *necessary copy analysis* is a forward analysis that collects information that is used to determine whether a copy should be generated before an array is modified. To simplify our description of the analysis, we consider only simple assignment statements of the form *lhs* = *rhs*. It is straightforward to show that our analysis works for both single (one *lhs* variable) and multiple assignment statements (multiple *lhs* variables). We describe the analysis by defining the following components.

3.3.1 Domain

The domain of the analysis' flow facts is the set of pairs that comprised of an array reference variable and the ID of the statement that allocates the memory for the array; henceforth called *allocators*. We write (a, s) if a may reference the array allocated at statement s.

3.3.2 Problem Definition

At a program point p, a variable references a shared array if the number of variables that reference the array is greater than one. An array update via an array reference variable

requires a copy if the variable *may* reference a shared array at p and at least one of the other variables that reference the same array is *live* after p. We assume that at each program point, the set of *live variables* has been computed.

3.3.3 Flow Function

$$\mathit{out}(S_i) = \mathit{gen}(S_i) \cup (\mathit{in}(S_i) - \mathit{kill}(S_i)).$$

Given the assignment statements of the forms:

$$S_i : a = \textbf{\textit{alloc}} \tag{3.1}$$

$$S_i : a = b \tag{3.2}$$

$$S_i : a(j) = x \tag{3.3}$$

$$S_i : a = f(\mathit{arg}_1, \mathit{arg}_2, ..., \mathit{arg}_n) \tag{3.4}$$

where S_i denotes a statement ID; ***alloc*** is a new memory allocation performed by statement S_i [1]; a, b are array reference variables; x is a *rvalue*; f is a function, $\mathit{arg}_1, \mathit{arg}_2, ..., \mathit{arg}_n$ denote the arguments passed into the function and the corresponding formal parameters are denoted with $p_1, p_2, ..., p_n$.

We partition $\mathit{in}(S_i)$ using allocators. The partition, $Q_i(m)$, containing flow entries for allocator m is:

$$Q_i(m) = \{(x, y) | (x, y) \in \mathit{in}(S_i) \wedge y = m\} \tag{3.5}$$

Now consider statements of type 3.2 above; if variable b has a reaching definition at S_i then there must exist some $(b, m) \in \mathit{in}(S_i)$ and there exists a non-empty $Q_i(m)$ such that $(b, m) \in Q_i(m)$.

In addition, if b may reference a shared array at S_i then $|Q_i(m)| > 1$. Let us call the set of all such $Q_i(m)$s, P_i. We write $P_i(a)$ for the set of Q_is obtained by partitioning $\mathit{in}(S_i)$ using the allocators of variable a.

Considering statements of the form 3.3, $P_i(a) \neq \emptyset$ implies that a copy of a must be generated before executing S_i and in that case, S_i is a *copy generator*. This means that after this statement, a will point to a new copy and no other variable will refer to this copy.

1. Functions such as *zeros*, *ones*, *rand* and *magic* are memory allocators in MATLAB.

We are now ready to construct a table of *gen* and *kill* sets for the four assignment statement kinds above. To simplify the table, we define:

$\mathit{Kill}_{\mathit{define}}(a) = \{(x,s) | (x,s) \in \mathit{in}(S_i) \wedge x = a\}$
$\mathit{Kill}_{\mathit{dead}} = \{(x,s) | (x,s) \in \mathit{in}(S_i) \wedge \textbf{\textit{not live}}(S_i, x)\}$
$\mathit{Kill}_{\mathit{update}}(a) = \{(x,s) | (x,s) \in \mathit{in}(S_i) \wedge x = a \wedge P_i(a) \neq \emptyset\}$
where ***live***(S_i, x) is a function that returns ***true*** if variable x is *live* at program point S_i and returns ***false*** otherwise.

Stmt	**Gen set**	**Kill set**
(3.1)	$\{(x,s) \mid x = a \wedge s = S_i \wedge \textbf{\textit{live}}(S_i, x)\}$	$\mathit{Kill}_{\mathit{define}}(a) \cup \mathit{Kill}_{dead}$
(3.2)	$\{(x,s) \mid x = a \wedge (y,s) \in \mathit{in}(S_i) \wedge y = b \wedge \textbf{\textit{live}}(S_i, x)\}$	$\mathit{Kill}_{\mathit{define}}(a) \cup \mathit{Kill}_{\mathit{dead}}$
(3.3)	$\{(x,s) \mid x = a \wedge s = S_i \wedge P_i(x) \neq \emptyset\}$	$\mathit{Kill}_{\mathit{update}}(a) \cup \mathit{Kill}_{deads}$
(3.4)	see $\mathit{gen}(f)$ below	$\mathit{Kill}_{\mathit{define}}(a) \cup \mathit{Kill}_{deads}$

Computing the *gen* set for a function call is not straightforward. Certain built-in functions allocate memory blocks for arrays; such functions are categorized as *alloc functions*. A question that arises is: does the return value of the called function reference the same shared array as a parameter of the function? If the return value references the same array as a parameter of the function then this sharing must be made explicit in the caller, after the function call statement. Therefore, the *gen* set for a function call is defined as:

$$\mathit{gen}(f) = \begin{cases} \{(a, S_i)\}, \text{ if } \textbf{\textit{live}}(S_i, a) \textbf{ \textit{and isAllocFunction}}(f) \\ \{(x,s) \mid x = a \wedge (\mathit{arg}_j, s) \in \mathit{in}(S_i) \wedge \textbf{\textit{live}}(S_i, x)\}, \\ \quad \text{if } \textbf{\textit{ret}}(f) \textbf{ \textit{aliases}} \ \mathit{param}_j(f),\ 0 < j \leq \textbf{\textit{size}}(\mathit{params}(f)), \\ \{(a, S_i)\}, \text{ if } \forall (p \in \mathit{params}(f)), \textbf{ \textit{not}} \ (\textbf{\textit{ret}}(f) \textbf{ \textit{aliases}} \ p) \\ \{(x,s) \mid x = a \wedge \mathit{arg} \in \mathit{args}(f) \wedge (\mathit{arg}, s) \in \mathit{in}(S_i) \wedge \textbf{\textit{live}}(S_i, x)\}, \\ \quad \textbf{\textit{otherwise}} \text{ (e.g., if } f \text{ is recursive)} \end{cases}$$

The first alternative generates a flow entry (a, S_i) if the *rhs* is an *alloc* function and the *lhs* (a) is live after statement S_i; this makes statement S_i an allocator. In the second alternative, the analysis requests the result of the necessary copy analysis on f from an analysis manager.[2] The manager caches the result of the previous analysis on a given function. From the result of the analysis on f, we determine the return variables of f that are aliases to the parameters of f and hence aliases to the arguments of f. This is explained in detail under the next section on Initialization. The return variable of f corresponds to the *lhs* (a) in statement type 3.4. Therefore, using the summary information of f, we generate new flow entries from those associated with the arguments that the return variable may reference provided that a is also *live* after S_i.

The third alternative generates $\{(a, S_i)\}$, if the return variable aliases no parameters of f. The fourth alternative is conservative: new flow entries are generated from those of *all* the arguments to f. This can happen if the call of f is recursive or f cannot be analyzed because it is neither a user-defined function nor an *alloc* function.

We chose a simple strategy for recursion because recursive functions occur rarely in MATLAB. In a separate study by our group, we found that out of 15,966 functions in 625 projects examined, only 48 functions (0.3%) are directly recursive. None of the programs in our benchmarks had recursive functions.

Therefore, we expect that the conservative option in the definition of *gen*(f) above will be rarely taken in practice.

3.3.4 Initialization

The input set for a function is initialized with a flow entry for each parameter and an additional flow entry (a shadow entry) for each parameter is also inserted. This is necessary in order to determine which of the parameters (if any) return variable references. We use a shadow entry to detect when a parameter that has not been assigned to any other variable is updated. At the entry to a function, the input set is given as

2. This uses the same analysis machinery as the type estimation in McJIT.

$\mathit{in}(\mathit{entry}) = \{(p, s)|p \in \mathit{params}(f) \wedge s = S_p\} \cup \{(p', s)|p \in \mathit{params}(f) \wedge s = S_p\}$.

We illustrate this scheme with an example. Given a function f, defined as:

```
function u = f(x, y)
  u = x;
end
```

the *in* set at the entry of f is $\{(x, S_x), (x', S_x), (y, S_y), (y', S_y)\}$ and at the end of the function, the *out* set is $\{(u, S_x), (x, S_x), (x', S_x), (y, S_y), (y', S_y)\}$.

We now know that u is an alias for x and encode this information as a set of integers. An element of the set is an integer representing the input parameter that the output parameter may reference in the function. In this example, the set is $\{1\}$ since x is the first (1) parameter of f. This is useful during a call of f. For instance, in `c = f(a, b);` we can determine that c is an alias for argument a by inspecting the summary information generated for f.

3.3.5 Simple Example

Let us illustrate how the analysis works with the following simple example.

```
1 function example1()
2     a = rand(15000);
3     b = a;
4     b(1) = 10;
5     a = [1:10];
6     disp(a (1:5));
7     disp(b (1:5));
8 end
```

Table 3.1 shows the flow information at each statement of the function, including the *gen*, *kill*, *in* and *out* sets. The statement number is shown in the first column of the table.

The analysis begins by initializing $\mathit{in}(S_2)$ to $\emptyset$ since the function does not have any parameters. The assignment statement S_2 is an allocator because function *rand* is an alloc function. Table 3.1 shows that despite the assignment in line 3, no copies should be generated before the assignment in line 4. This is because variable a defined in line 2 is no longer *live* after line 3 hence, S_4 is not a copy generator according to our definition.

#	Gen set	Kill set	In set	Out set
2	$\{(a, S_2)\}$	$\emptyset$	$\emptyset$	$\{(a, S_2)\}$
3	$\{(b, S_2)$	$\{(a, S_2)\}$	$\{(a, S_2)\}$	$\{(b, S_2)\}$
4	$\emptyset$	$\emptyset$	$\{(b, S_2)\}$	$\{(b, S_2)\}$
5	$\{(a, S_5)$	$\emptyset$	$\{(b, S_2)\}$	$\{(b, S_2), (a, S_5)\}$

Table 3.1 – Forward Analysis result for example1.

3.3.6 *if-else* Statement

So far we have been considering sequences of statements. As our analysis is done directly on a simplified AST, analyzing an ***if-else*** statement simply requires that we analyze all the alternative blocks and merge the result at the end of the ***if-else*** statement using the merge operator ($\cup$).

3.3.7 Loops

We compute the input set reaching a loop and the output set exiting a loop using standard flow analysis techniques, that is, we merge the input flow set from the loop's entry with the output set from the loop back-edge until a fixed point is reached.

To analyse a loop more precisely, we implemented a context-sensitive loop analysis that distinguishes the sharing of arrays that are initiated outside the loop from those initiated within the loop, and from those initiated in different iterations of the loop. This distinction is necessary in certain cases to prevent unneeded copies from being generated [LH10]. We found, however, that real MATLAB programs did not require the context-sensitivity to achieve good results. The standard approach is sufficient for typical MATLAB programs.

3.4 Copy Placement Analysis

In the previous section, we described the forward analysis which determines whether a copy should be generated before an array is updated. One could use this analysis alone to insert the copy statements, but this may not lead to the best placement of the copies and

may lead to redundant copies. The backward *copy placement analysis* determines a better placement of the copies, while at the same time ensuring safe updates of a shared array. Examples of moving copies include hoisting copies out of if-then constructs and out of loops.

The intuition behind this analysis is that often it is better to perform the array copy close to the statement which created the sharing (i.e. statements of the form *a = b*) rather than just before the array update statements (i.e. statements of the form *a(i) = b*) that require the copy. In particular, if the update statement is inside a loop, but the statement that created the sharing is outside the loop, then it is much better to create the copy outside of the loop. Thus, the *copy placement analysis* is a backward analysis that pushes the necessary copies upwards, possibly as far as the statement that created the sharing.

3.4.1 Abstraction

A copy entry is a three-tuple:

$$e =< copy\_loc, var, alloc\_site > \tag{3.6}$$

where *copy_loc* denotes the ID of the node that generates the copy, *var* denotes the variable containing a reference to the array that should be copied, and *alloc_site* is the allocation site where the array referenced by *var* was allocated. We refer to the three components of the three-tuple as *e.copy_loc*, *e.var*, and *e.alloc_site*.

Let C denote the set of all copies generated by a function.

Given a function, the analysis begins by traversing the block of statements of the function backward. The domain of the analysis' flow entries is the set of copy objects and the merge operator is intersection ($\cap$).

Define C_{out} as the set of copy objects at the exit of a block and C_{in} as the set of copy objects at the entrance of a block. Since the analysis begins at the end of a function, C_{out} is initialized to $\emptyset$. The rules for generating and placing copies are described here.

3.4.2 Statement Sequence

Given a sequence of statements, we are given a C_{out} for this block and the analysis traverses backwards through the block computing a C_{in} for the block. As each statement is traversed the following rules are applied for the different kinds of the assignment statements in the sequence. The sets *in*(S_i), $Q_i(m)$, $P_i(a)$ are defined in Section 3.3.

Rule 1: array updates, $S_i : a(y) = x$: Given that the array variable of the *lhs* of statement S_i is a, when a statement of this form is reached, we add a copy for each partition for a shared array to the current copy set. Thus

$$C_{in} := C_{in} \cup \begin{cases} \emptyset & \text{if } P_i(a) = \emptyset \\ \{< s, x, y > | s = S_i \wedge x = a \wedge Q_i(y) \in P_i(x)\} & \textbf{\textit{otherwise}} \end{cases}$$

Rule 2: array assignments, $S_j : a = b$: If $\forall e \in C_{in}$(*e.var* $\neq a$ ***and*** *e.var* $\neq b$), and $\forall e \in C_{out}$(*e.var* $\neq a$ ***and*** *e.var* $\neq b$), we skip the current statement. However, if in the current block, $\exists e \in C_{in}$(*e.var* $= a$ ***or*** *e.var* $= b$), we remove e from the current copy flow set C_{in}. This means that the copy has been placed at its current location — the location specified in copy entry e. Otherwise, if $\exists e \in C_{out}$(*e.var* $= a$ ***or*** *e.var* $= b$), we perform the following:

if $P_j(a) = \emptyset$**,** this is usually the case, we move the copy from the statement *e.copy_loc* to S_j and remove e from the flow set. The copy e has now been finally placed.

if $P_j(a) \neq \emptyset$**,** $\forall(Q_i(m) \in P_j(a))$, we add a runtime equality test for a against the variable x ($x \neq a$) of each member of $Q_i(m)$ at the statement *e.copy_loc*. Since $P_j(a) \neq \emptyset$, there is at least a definition of a that reaches this statement and for which a references a shared array. In addition, because copy e was generated after the current block there are at least two different paths to statement *e.copy_loc*, the current location of e. We place a copy of e at the current statement S_j and remove e from the flow set. Note that two copies of e have been placed; one at *e.copy_loc* and another at S_j. However, runtime guards have also been placed at *e.copy_loc*, ensuring that only one of these two copies materializes at run time.

The following code snippet illustrates this scenario.

```
1   b = [2, 4, 8];
2   a = b;
3   if (cond)
4       c = rand(10);
5        ...
6       a = c;
7   end
8   a(i) = 10;
9   disp(a);
10  disp(b);
```

Statement S_2 dominates statement S_4; if the ***then*** block is taken then, at statement S_8 (the array update statement), a will reference the array allocated at S_4. Otherwise, a will reference the array allocated at S_1. Thus, by placing a copy after S_6, it is guaranteed that a is unique if the program takes the path through S_6 to S_8; and the update at S_8 is therefore safe and no copy will be generated at S_8 because the runtime guard will be false. However, if this path is not taken, then the guard at S_8 will be true and a copy will be generated.

We expect that such guards will not usually be needed, and in fact none of our benchmarks required any guards.

3.4.3 *if-else* Statements

Let C_{if} and C_{else} denote the set of copies generated in an ***if*** and an ***else*** block respectively. First we compute

$$C' := (C_{out} \cap C_{else} \cap C_{if})$$

Then we compute the differences

$$C'_{out} := C_{out} \setminus C'; \quad C'_{else} := C_{else} \setminus C'; \quad C'_{if} := C_{if} \setminus C'$$

to separate those copies that do not intersect with those in other blocks but should nevertheless be propagated upward. Since the copies in the intersection will be relocated, they are removed from their current locations.

And finally,

$$C_{in} := C'_{out} \cup C'_{else} \cup C'_{if} \cup \{< s, e.var, e.alloc\_site > | s = S_{IF} \wedge e \in C'\}$$

Note that a copy object e with its first component set to S_{IF} is attached to the *if-else* statement S_{IF}. That means if these copies remain at this location, the copies should be generated before the *if-else* statement.

3.4.4 Loops

The main goal here is to identify copies that could be moved out of a loop. To place copies generated in a loop, we apply the rules for statement sequence and the ***if-else*** statement. The analysis propagates copies upward from the inner-most loop to the outer-most loop and to the main sequence until either loop dependencies exist in the current loop or it is no longer possible to move the copy according to Rule 2 in Section 3.4.2.

A disadvantage of propagating the copy outside of the loop is that if none of the loops that require copies is executed then we would have generated a useless copy. However, the execution is still correct. For this reason, we assume that a loop will *always* be executed and generate copies outside loops, wherever possible. This is a reasonable assumption because a loop is typically programmed to execute. With this assumption, there is no need to compute the intersection of C_{loop} and C_{out}. Hence

$$C_{in} := C_{out} \cup \{< s, e.var, e.alloc\_site > | s = S_{loop} \wedge e \in C_{loop}\})$$

3.5 Using the Analyses

This section illustrates how the combination of the forward and the backward analyses is used to determine the actual copies that should be generated. First consider the following program, *test3*. Table 3.2 (a) shows the result of the forward analysis.

```
1  function test3 ()
2    a = [1:5];
3    b = a;
4    i = 1;
5    if (i > 2)    % I
6      a(1) = 100;
7    else
8      a(1) = 700;
9    end
10   a(1) = 200;
11   disp(a);
12   disp(b);
13 end
```

#	Gen set	In	Out
2	$\{(a, S_2)\}$	$\emptyset$	$\{(a, S_2)\}$
3	$\{(b, S_2)\}$	$\{(a, S_2)\}$	$\{(a, S_2)(b, S_2)\}$
6	$\{(a, S_6)\}$	$\{(a, S_2), (b, S_2)\}$	$\{(b, S_2)(a, S_6)\}$
8	$\{(a, S_8)\}$	$\{(a, S_2), (b, S_2)\}$	$\{(b, S_2), (a, S_8)\}$
10	$\emptyset$	$\{(b, S_2), (a, S_6), (a, S_8)\}$	$\{(b, S_2), (a, S_6), (a, S_8)\}$

(a) Necessary Copy Analysis Result for *test3*.

#	C_{out}	C_{in}	Current Result
10	$\emptyset$	$\emptyset$	$\emptyset$
8	$\emptyset$	$\{< S_8, a, S_2 >\}$	$\{(a, S_8)\}$
6	$\emptyset$	$\{< S_6, a, S_2 >\}$	$\{(a, S_6)\}$
I	$\emptyset$	$\{< S_I, a, S_2 >\}$	$\{(a, S_I)\}$
3	$\{< S_I, a, S_2 >\}$	$\emptyset$	$\{(a, S_I)\}$
2	$\emptyset$	$\emptyset$	$\{(a, S_I)\}$

(b) Copy Placement Analysis Result for *test3*.

Table 3.2 – Necessary Copy and Copy Placement Analyses for *test3*.

Table 3.2 (b) gives the result of the backward analysis. The I used in line 5 of *test3* stands for the ***if-else*** statement in *test3*. The analysis begins from line 12 of *test3*. The *out* set C_{out} is initially empty. At line 10, C_{out} is still empty. When the ***if-else*** statement is reached, a copy of C_{out} ($\emptyset$) is passed to the *Else* block and another copy is passed to the *If* block. The copy $\{< S_8, a, S_2 >$ is generated in the *Else* block because $|Q(S_2) = \{(a, S_2), (b, S_2)\}| = 2$, hence $P_i(a) \neq \emptyset$. Similarly $< S_6, a, S_2 >$ is generated in the *If* block.

By applying the rule for ***if-else*** statement described in Section 3.4.3, the outputs of the *If* and the *Else* blocks are merged to obtain the result at S_I (the ***if-else*** statement). Applying Rule 2 for statement sequence (Section 3.4.2) in S_3, $< S_I, a, S_2 >$ is removed from C_{in} and the analysis terminates at S_2. The final result is that a copy must be generated before the ***if-else*** statement instead of generating two copies, one in each block of the ***if-else*** statement. This example illustrates how common copies generated in the alternative blocks of an ***if-else*** statement could be combined and propagated upward to reduce code size.

The second example, *tridisolve* is a MATLAB function from [Cle04]. The forward analysis information is shown in Table 3.3. The table shows the *gen* and *in* sets at each relevant assignment statement of *tridisolve*. The results in different loop iterations are shown using a subscript to represent loop iteration. For example, the row number 25_2 refers to the result at the statement labelled S_{25} in the second iteration. The analysis reached a fixed point after the third iteration.

Listing 3.1 – A MATLAB function (*tridisolve*).

```
function x = tridisolve (a,b,c,d)
% TRIDISOLVE Solve tridiagonal system of equations.
20: x = d;
21: n = length(x);
    for j = 1:n-1          %F_1
      mu = a(j)/b(j);
25:   b(j+1) = b(j+1) - mu*c(j);
26:   x(j+1) = x(j+1) - mu*x(j);
    end
29: x(n) = x(n)/b(n);
    for j = n-1:-1:1       %F_2
31:   x(j) = (x(j)-c(j)*x(j+1))/b(j);
    end
```

At the function's entry, the *in* set is initialized with two flow entries for each parameter of the function as outlined in Section 3.3. The analysis continues by generating the *gen*, *in* and *out* sets according to the rules specified in Section 3.3. Notice that statement S_{25} is an allocator because $P_{25}(b) \neq \emptyset$ since $|Q_{25}(S_b)| = |\{(b, S_b, 0), (b', S_b, 0)\}| > 1$. Similarly, S_{26} and S_{29} are also allocators. This means that generating a copy of the array referenced by the variable b just before executing the statement S_{25} ensures a safe update of the array. The same is true of the array referenced by the variable x in lines 26 and 29. However, are these the best points in the program to generate those copies? Could the number of copies be reduced? We provide the answers to these questions when we examine the results of the backward analysis.

Table 3.4 shows the copy placement analysis information at each relevant statement of *tridisolve*. Recall that the placement analysis works by traversing the statements in each block of a function backward. In the case of *tridisolve*, the analysis begins in line 31 in the second ***for*** loop of the function. The set C_{out} is passed to the loop body and is initially empty. The set C_{in} stores all the copies generated in the block of the *for* statement. Line 31 is neither a definition nor an allocator, therefore no changes are recorded at this stage of the analysis.

#	**Gen**	**In**
20	$\{(x, S_d, 0)\}$	$\{(a, S_a, 0), (a', S_a, 0), (b, S_b, 0), (b', S_b, 0), (c, S_c, 0), (c', S_c, 0), (d, S_d, 0), (d', S_d, 0)\}$
25_1	$\{(b, S_{25}, 1)\}$	$\{(a, S_a, 0), (a', S_a, 0), (b, S_b, 0), (b', S_b, 0), (c, S_c, 0), (c', S_c, 0), (d', S_d, 0), (x, S_d, 0)\}$
26_1	$\{(x, S_{26}, 1)\}$	$\{(a, S_a, 0), (a', S_a, 0), (b', S_b, 0), (c, S_c, 0), (c', S_c, 0), (d', S_d, 0), (x, S_d, 0), (b, S_{25}, 1)\}$
25_2	$\{(b, S_{25}, 2)\}$	$\{(a, S_a, 0), (a', S_a, 0), (b, S_b, 0), (b', S_b, 0), (c, S_c, 0), (c', S_c, 0), (d', S_d, 0), (x, S_d, 0), (b, S_{25}, 1), (x, S_{26}, 1)\}$
26_2	$\{(x, S_{26}, 2)\}$	$\{(a, S_a, 0), (a', S_a, 0), (b', S_b, 0), (c, S_c, 0), (c', S_c, 0), (d', S_d, 0), (x, S_d, 0), (b, S_{25}, 2), (x, S_{26}, 1)\}$
25_3	$\{(b, S_{25}, 3)\}$	$\{(a, S_a, 0), (a', S_a, 0), (b, S_b, 0), (b', S_b, 0), (c, S_c, 0), (c', S_c, 0), (d', S_d, 0), (x, S_d, 0), (b, S_{25}, 2), (x, S_{26}, 2)\}$
26_3	$\{(x, S_{26}, 3)\}$	$\{(a, S_a, 0), (a', S_a, 0), (b', S_b, 0), (c, S_c, 0), (c', S_c, 0), (d', S_d, 0), (x, S_d, 0), (b, S_{25}, 3), (x, S_{26}, 2)\}$
29	$\{(x, S_{29}, 0)\}$	$\{(a', S_a, 0), (b, S_b, 0), (b', S_b, 0), (c, S_c, 0), (c', S_c, 0), (d', S_d, 0), (x, S_d, 0), (b, S_{25}, 3), (x, S_{26}, 3)\}$
31_1	$\emptyset$	$\{(a', S_a, 0), (b, S_b, 0), (b', S_b, 0), (c, S_c, 0), (c', S_c, 0), (d', S_d, 0), (b, S_{25}, 3), (x, S_{29}, 0)\}$
31_2	$\emptyset$	$\{(a', S_a, 0), (b, S_b, 0), (b', S_b, 0), (c, S_c, 0), (c', S_c, 0), (d', S_d, 0), (b, S_{25}, 3), (x, S_{29}, 0)\}$

Table 3.3 – Necessary Copy Analysis Result.

#	C_{out}	C_{in}	**Current Result**
31	$\emptyset$	$\emptyset$	$\emptyset$
F_2	$\emptyset$	$\emptyset$	$\emptyset$
29	$\emptyset$	$\{(S_{29}, a, S_d)\}$	$\{(x, S_{29})\}$
26	$\{(S_{29}, x, S_d)\}$	$\{(S_{26}, x, S_d)\}$	$\{(x, S_{29}), (x, S_{26})\}$
25	$\{(S_{29}, x, S_d)\}$	$\{(S_{25}, b, S_b), (S_{26}, x, S_d)\}$	$\{(x, S_{29}), (x, S_{26}), (b, S_{25})\}$
F_1	$\{(S_{29}, x, S_d)\}$	$\{(S_{F_1}, x, S_d), (S_{25}, b, S_b)\}$	$\{(x, S_{F_1}), (b, S_{25})\}$
20	$\emptyset$	$\{(S_{25}, b, S_b)\}$	$\{(x, S_{F_1}), (b, S_{25})\}$
0	$\emptyset$	$\emptyset$	$\{(x, S_{F_1}), (b, S_0)\}$

Table 3.4 – Copy Placement Analysis Result for *tridisolve*.

At the beginning of loop F_2, the analysis merges with the main path and the result at this point is shown in row F_2. Statement S_{29} generated a copy as indicated by the forward analysis, therefore C_{in} is updated and the result set is also updated. The analysis then branches off to the first loop and the current C_{in} is passed to the loop's body as C_{out}. The copies generated in loop F_1 are stored in C_{in}, which is then merged with C_{out} at the beginning of the loop to arrive at the result in row F_1. The result set is also updated accordingly; at this stage, the number of copies has been reduced by 1 as shown in the column labelled *Current Result* of Table 3.4. The copy flow set that reaches the beginning of the function is non-empty. This suggests that the definition or the allocator of the array variables of the remaining entries could not be reached. Therefore, the array variables of the flow entries *must* be the parameters of the function and the necessary copy should be generated at the function's entry. Hence, a copy of the array referenced by b must be generated at the entry of *tridisolve*.

3.6 Name Resolution

In Section 2.1, we mentioned that MATLAB uses the same syntax for both function calls and array accesses. Here, we discuss the compilation problem posed by this strategy.

An obvious advantage of using identical syntax is that a data structure initially implemented as an array could be re-implemented as a function without changing the array accesses. A disadvantage of this strategy, however, is that it makes it difficult to determine statically whether an expression is a function call or an array access, thus making analyses too conservative. For instance, in the statement below, is b a function or an array?

```
m = b(c, d);
```

Without a suitable analysis, it is hard to tell whether $b(c, d)$ is a function call or an array access. The forward analysis described in Section 3.3 relies on the McVM type inference analysis [CBHV10, CB09] to determine the type of a symbol. In the simple assignment statement above, the analysis needs to know whether the variables m, c and d are arrays. Furthermore, if b is a function and m, c and d are arrays, the analysis needs to know whether m references the same array as c or d. The forward analysis requests the type information of b and proceeds to analyse b if the result of the look-up indicates that b is a function.

3.7 Experimental Results

To evaluate the effectiveness of our approach, we set up experiments using benchmarks collected from disparate sources, including those from [RGG+96, Cle04, Pre86]. Table 3.5 gives a short description of each benchmark, together with, a summary of the results of our analyses, which we discuss in more detail in the following subsections. For all the experiments described in this chapter, we ran the benchmarks with their smallest input size on an AMD Athlon™ 64 X2 Dual Core Processor 3800+, 4GB RAM computer running Linux operating system; GNU Octave, version 3.2.4; MATLAB, version 7.9.0.529 (R2009b) [3] and McVM/McJIT, version 0.5.

The purpose of our experiments was three-fold. First, we wanted to measure the number of array updates and copies performed by the benchmarks at run time using existing systems (Section 3.7.1). Knowing the number of updates gives an idea of how many dynamic checks a reference-counting-based (RC) scheme for lazy copying, such as used by Octave

3. We used the later versions of MATLAB for the experiments described in the following chapters.

and Mathworks' MATLAB, need to perform. Recall that our approach does not usually require any dynamic checks. Knowing the number of copies generated by such systems allows us to verify that our approach does not increase the number of copies as compared to the reference-counting-based approaches. Secondly, we would like to measure the amount of overhead generated in reference-counting-based systems (Section 3.7.2). Finally, we would like to assess the impact of our static analyses in terms of their ability to minimize the number of copies (Section 3.7.3).

3.7.1 Dynamic Counts of Array Updates and Copies

Our first measurements were designed to measure the number of array updates and array copies that are required by existing reference-counting-based systems, Octave and Mathworks' MATLAB. Since we had access to the open-source Octave system we were able to instrument the interpreter and make the measurements directly. However, the Mathworks' implementation of MATLAB is a proprietary system and thus we were unable to instrument it to make direct measurements. Instead, we developed an alternative approach by instrumenting the benchmark programs themselves via aspects using our ASPECTMATLAB compiler *amc* [ADDH10]. Our aspect [4] defines all the patterns for the relevant points in a MATLAB program including all array definitions, array updates, and function calls. It also specifies the actions that should be taken at these points in the source program. In effect, the aspect computes all of the information that a reference-counting-based scheme would have, and thus can determine, at run time, when an array update triggers a copy because the number of references to the array is greater than one. The aspect thus counts all array updates and all copies that would be required by a reference-counting-based system.

4. This aspect is available at: http://www.sable.mcgill.ca/mclab/copy_analysis.html. It is also listed in Appendix B.

5. The benchmarks are also available at: www.sable.mcgill.ca/mclab/mcvm_mcjit.html.

Benchmark		# Array Updates	# Copies				
			Lower Bound		With Analyses		
			Aspect	Octave	Naive	QC	CA
adpt	adaptive quadrature using Simpson's rule	19624	0	0	12223	12223	0
capr	capacitance of a transmission line using finite difference and Gauss-Seidel iteration	9790800	10000	10000	40000	20000	10000
clos	transitive closure of a directed graph	2954	0	0	2	2	0
crni	Crank-Nicholson solution to the one-dimensional heat equation	21143907	4598	6898	11495	6897	4598
dich	Dirichlet solution to Laplace's equation	6935292	0	0	0	0	0
fdtd	3D FDTD of a hexahedral cavity with conducting walls	803	0	0	5400	5400	0
fft	fast fourier transform	44038144	1	1	2	2	1
fiff	finite-difference solution to the wave equation	12243000	0	0	0	0	0
mbrt	Mandelbrot set	5929	0	0	0	0	0
nb1d	N-body problem coded using 1d arrays for the displacement vectors.	55020	0	0	10984	10980	0
nb3d	N-body problem coded using 3d arrays for the displacement vectors.	4878	0	0	5860	5858	0
nfrc	computes a newton fractal in the complex plane -2..2,-2i..2i	12800	0	0	6400	6400	0
trid	Solve tridiagonal system of equations	2998	2	2	5	2	2

Table 3.5 – Benchmarks and the results of the copy analysis [5]

In Table 3.5 the column labelled *# Array Updates* gives the total number of array updates executed. The column *# Copies* shows the number of copies generated by the benchmarks under Octave (reported as *Octave* in the table) and MATLAB (column labelled *Aspect*). The column *# Copies* is split into two: *Lower Bound* and *With Analyses*. The number of copies generated by Octave and MATLAB (Aspect) are considered the expected lower bounds (since they perform copies lazily, and only when required) and are therefore grouped under *Lower Bound* in the table. [6]

At a high-level, the results in Table 3.5 show that our benchmarks often perform a significant number of array updates, but very few updates trigger copies. We observed that no copies were generated in ten out of the thirteen benchmarks. This low rate for array copies is not surprising because MATLAB programmers tend to avoid copying large objects and often only read from function parameters. *With Analyses* is comprised of three columns, *Naive*, *QC*, and *CA* representing respectively, the number of copies generated in our naive system, with the QC phase, and with the copy analysis phase. We return to these results in Section 3.7.3.

3.7.2 The Overhead of Dynamic Checks

With the reference-counting-based approaches, a dynamic check is needed for each array update, in order to test if a copy is needed. Our counts indicated that several of our benchmarks had a high number of updates, but no copies were required. We wanted to measure the overhead for all of these redundant dynamic checks. The ideal measurement would have been to time the redundant checks in a JIT-based system that used reference-counting, such as Mathworks' MATLAB. Unfortunately we do not have access to such a system. Instead we performed two similar experiments, as reported in Table 3.6, for three benchmarks with a high number of updates and no required copies (`dich`, `fiff` and `mbrt`).

6. Note that for the benchmark `crni` Octave performs 6898 copies, whereas the lower bound according to the Aspect is 4598. We verified that Octave is doing some spurious copies in this case, and that the Aspect number is the true lower bound.

	McVM						Octave(O)		
	McJIT		McJIT(+RC)		Overhead(%)		Time(s)		Overhead
Bmark	t(s)	# LLVM	t(s)	# LLVM	time	size	O(+RC)	O(-RC)	(%)
dich	0.18	546	0.27	625	47.37	14.47	425.05	408.08	4.16
fiff	0.39	388	0.52	415	33.72	6.96	468.64	438.69	6.83
mbrt	5.06	262	5.65	271	11.69	3.44	34.91	31.95	9.29

Table 3.6 – Overhead of Dynamic Checks.

We first created a version of Octave that does not insert dynamic checks before array update statements. In general this is not safe, but for these three benchmarks we knew no copies were needed, and thus removing the checks allowed us to measure the overhead without breaking the benchmarks. The column labelled *O(+RC)* gives the execution time with dynamic checks and the column labelled *O(-RC)* gives the times when we artificially removed the checks. The difference gives us the overhead, which is between 4% and 9% for these benchmarks. Although this is not a huge percentage, it is not negligible. Furthermore, we felt that the absolute time for the checks was significant and would be even more significant in a JIT system which has many fewer other overheads.

To measure overheads in a JIT context, we modified McJIT to include enough reference-counting machinery to measure the overhead of the checks (remember that McVM is garbage-collected and does not normally have reference counts). For the modified McVM we added a field to the array object representation to store reference counts (which is set to zero for the purposes of this experiment) and we generated LLVM code for a runtime check before each array update statement. Table 3.6 shows, in time and code size, the amount of overhead generated by redundant checks. The column labelled *McJIT* is the original McJIT and the column labelled *McJIT(+RC)* is the modified version with the added checks. We measured code size using the number of LLVM instructions (*# LLVM*) and execution time overhead in seconds. For these benchmarks the code size overhead was 3% to 14% and the running time overhead ranged from 12% to 47%.

Our conclusions is that the dynamic checks for a reference-counting-based scheme can be quite significant in both execution time and code size, especially in the context of a JIT. Thus, although the original motivation of our work was to enable a garbage-collected VM

that did not require reference counts, we think that our analyses could also be useful to eliminate unneeded checks in reference-counting-based systems.

3.7.3 Impact of our Analyses

Let us now return to the number of copies required by our analyses, which are given in the last three columns of Table 3.5. As a reminder, our goal was to achieve the same number of copies as the lower bound.

The column labelled *Naive* gives the number of copies required with a naive implementation of MATLAB's copy semantics, where a copy is inserted for each parameter, each return value and each copy statement, where the *lhs* is an array. Clearly this approach leads to many more copies than the lower bound.

The column labelled *CA* gives the number of copies when both phases of our static analyses are enabled. We were very pleased to see that for our benchmarks, the static analyses achieved the same number of copies as the lower bound, without requiring any dynamic checks. The column labelled *QC* shows the number of copies when only the QuickCheck phase is enabled. Although the QuickCheck does eliminate many unneeded copies, it does not achieve the lower bound. Thus, the second stage is really required in many cases.

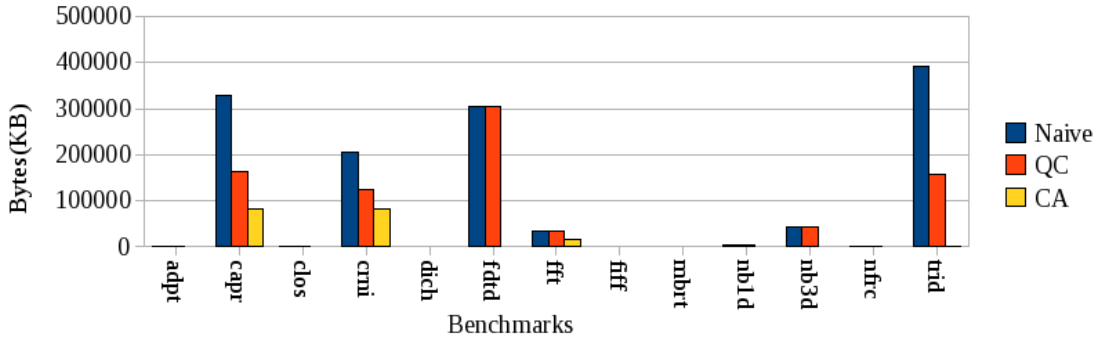


Figure 3.2 – The total bytes of array data copied by the benchmarks under the three options.

To show the impact copies have on execution performance, we measured the total bytes of array data copied by a benchmark together with its corresponding execution time. These are shown in Figure 3.2 and Table 3.7 for *Naive*, *QC* and *CA*. The columns $\frac{Naive}{QC}$ and $\frac{Naive}{CA}$

Bmark	**Naive**	**QC**	**CA**	$\frac{Naive}{QC}$	$\frac{Naive}{CA}$
adpt	1.57	1.57	1.61	1.00	0.98
capr	1.54	0.91	0.58	1.70	2.66
clos	0.49	0.49	0.48	0.99	1.01
crni	135.09	140.35	131.62	0.96	1.03
dich	0.18	0.18	0.18	1.00	1.00
fdtd	3.79	3.78	2.80	1.00	1.35
fft	1.50	1.50	1.47	1.00	1.02
fiff	0.39	0.39	0.39	0.99	0.99
mbrt	5.06	5.12	5.04	0.99	1.00
nb1d	0.48	0.48	0.45	1.00	1.07
nb3d	0.48	0.48	0.36	1.00	1.35
nfrc	3.23	3.23	3.25	1.00	0.99
trid	1.57	1.04	1.02	1.51	1.53

Table 3.7 – Benchmarks against the total execution times in seconds.

of Table 3.7 show respectively how many times QC and CA perform better than *Naive*. The table shows that *CA* generally outperforms *QC* and *Naive*. Copying large arrays affects execution performance and the results in Table 3.7 validate this claim. Where a significant number of bytes were copied by the naive implementation, for example, *capr*, *crni* and *fdtd*, *CA* performs better than both *Naive* and *QC*. In the three benchmarks that do not generate copies, the performance of *CA* is comparable to *Naive* and *QC*. This shows that the overhead of *CA* is low. It is therefore clear from the results of our experiments that the naive implementation generates significant overhead and is therefore unsuitable for a high-performance system.

Impact of the First Phase We measured the number of functions that are completely resolved by the first phase of our approach — in terms of finding all the necessary copies required to guarantee copy semantics. We found that out of the 23 functions in the benchmark set, the first stage (i.e., QuickCheck) was only able to resolve about 17% of the functions. None of the benchmarks was resolved completely by QC. The main reason for this poor

performance is that the first phase cannot resolve functions that return arrays to their callers. Like most MATLAB programs, most of the functions in the benchmarks return arrays. This really shows that the second stage is actually required to completely determine the needed copies by typical MATLAB programs.

So, the bottom line is that a very low fraction of array updates result in copies, and frequently no copies are necessary. For our benchmark set, our static analysis determined the needed number of copies, while at the same time avoiding all the overhead of dynamic checks. Furthermore, our approach does not require reference counting and thus enables an efficient implementation of array copy semantics in garbage-collected systems like McVM.

3.8 Summary

In this chapter we have presented an approach for using static analysis to determine where to insert array copies in order to implement the array copy semantics in MATLAB. Unlike previous approaches, which used a reference-counting scheme and dynamic checks, our approach is implemented as a pair of static analysis phases in the McJIT compiler. The first phase implements simple analyses for detecting read-only parameters and standard copy elimination, whereas the second phase consists of a forward *necessary copy analysis* that determines which array update statements trigger copies, and a backward *copy placement analysis* that determines good places to insert the array copies. All of these analyses have been implemented as structured-based analyses on the McJIT intermediate representation.

Our approach does not require frequent dynamic checks, nor do we need the space and time overheads to maintain the reference counts. Our approach is particularly appealing in the context of a garbage-collected VM, such as the one we are working with. However, similar techniques could be used in a reference-counting-based system to remove redundant checks. Our experimental results validate that, on our benchmark set, we do not introduce any more copies than the reference-counting approach, and we eliminate all dynamic checks.

Chapter 4
A Modular Approach to On-Stack Replacement in LLVM

Virtual machines (VMs) with Just-in-Time (JIT) compilers have become common place for a wide variety of languages. Such systems have an advantage over static compilers in that compilation decisions can be made on-the-fly and they can adapt to the characteristics of the running program. On-stack replacement (OSR) is one approach that has been used to enable on-the-fly optimization of functions/methods [HCU92, FQ03, PVC01, SK06]. A key benefit of OSR is that it can be used to interrupt a long-running function/method (without waiting for the function to complete), and then restart an optimized version of the function at the program point and state at which it was interrupted.

As mentioned in Chapter 2, LLVM is an open compiler infrastructure that can be used to build JIT compilers for VMs [LA04, llv12]. It supports a well-defined code representation known as the LLVM IR, as well as supporting a large number of optimizations and code generators. LLVM has been used in production systems, as well as in many research projects. For instance, MacRuby is an LLVM-based implementation of Ruby on Mac OS X core technologies [1]; Rubinius [2] is another implementation of Ruby based on LLVM JIT. Unladen-swallow is a fast LLVM implementation of Python. [3] VMKit [4] is an LLVM-based

1. http://macruby.org/
2. http://rubini.us/
3. http://code.google.com/p/unladen-swallow/
4. Previously http://vmkit.llvm.org/ and now http://vmkit2.gforge.inria.fr/

project that works to ease the development of new language VMs, and which has three different VMs currently developed (Java, .Net, and a prototype R implementation). A common theme of these diverse projects is that they could benefit from further on-the-fly optimizations, but unfortunately LLVM does not support OSR-based optimizations. Indeed, we agree with the developers of VMKit who believe that using OSR would enable them to speculate and develop runtime optimizations that can improve the performance of their VMs. [5] Thus, given the value of and need for OSR and the wide-spread adoption of LLVM in both industry and academia, our research work aims to fill this important void and provide an approach and modular implementation of OSR for LLVM.

Implementing OSR in a non-Java VM and general-purpose compiler toolkits such as LLVM requires novel approaches. Some of the challenges to implementing OSR in LLVM include:

(1) Deciding at what point should the program be interrupted and how should such points be expressed within the existing design of LLVM, without changing the LLVM IR.

(2) The static single-assignment (SSA) nature of the LLVM IR requires correct updates of control flow graphs (CFGs) of LLVM code, thus program transformations to handle OSR-related control flow must be done carefully and fit into the structure imposed by LLVM.

(3) LLVM generates a fixed address for each function; how then should the code of a new version of the running function be made accessible at the old address without recompiling the callers of the function? This was actually a particularly challenging issue to solve.

(4) The OSR implementation must provide a clean integration with LLVM's capabilities for function inlining.

(5) As there are many users of LLVM, the OSR implementation should not require modifications to the existing LLVM installations. Ideally the OSR implementation could just be added to an LLVM installation without requiring any recompilation of the installation.

5. Private communication with the authors, October 2012.

We addressed these and other challenges by developing a modular approach to implementing OSR that fits naturally in the LLVM compiler infrastructure.

To illustrate a typical use of our OSR implementation, we have used the implementation to support a selective dynamic inlining optimization in a MATLAB VM. MATLAB [Mat09b] is a popular platform for programming scientific applications [Mol06]. It is a dynamic language designed for manipulation of matrices and vectors, which are common in scientific applications [Cle04]. The dynamic features of the language, such as dynamic typing and loading, contribute to its appeal but also make an efficient compilation difficult. MATLAB programs often have potentially long-running loops, and because its optimization can benefit greatly from on-the-fly information such as types and array shapes, we believe that it is an ideal language for OSR-based optimizations. Thus, we wanted to experiment with this idea in McVM/McJIT [CBHV10, McL12], an open source VM and JIT for MATLAB, which is built upon LLVM.

The main contributions of this chapter are:

Modular OSR in LLVM: We have designed and implemented OSR for LLVM. Our approach provides a clean API for JIT compiler writers using LLVM and clean implementation of that API, which integrates seamlessly with the standard LLVM distribution and that should be useful for a wide variety of applications of OSR.

Integrating OSR with inlining in LLVM: We show how we handle the case where the LLVM inliner inlines a function that contains OSR points.

The rest of the chapter is organized as follows. In Section 4.1, we classify OSR techniques according to their runtime transition capabilities. In Section 4.2, we outline the application programming interface (API) and demonstrate the usage of our OSR module, from a JIT compiler writer's point of view. In Section 4.3, we describe the implementation of our API and the integration of inlining. We conclude the chapter in Section 4.4.

4.1 OSR Classification

The term OSR is used in the literature [HCU92, PVC01, FQ03, AAB+05, SK06] to describe a variety of similar, but different, techniques for enabling an on-the-fly transition

from one version of running code to another semantically equivalent version. To see how these existing techniques relate to each other, and to our proposed OSR implementation, we propose a classification of OSR transitions, as illustrated in Figure 4.1.

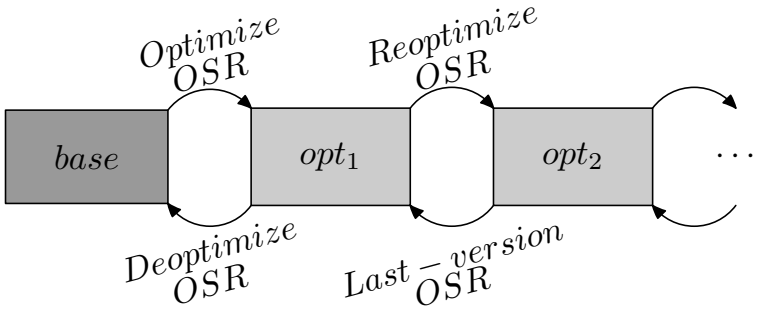


Figure 4.1 – OSR classification.

In most systems with OSR support, the execution of the running code often begins with interpretation or the execution of the code compiled by a non-optimizing base-line compiler. We refer to this version of the running code as the *base* version. This is shown in the darker shaded block of Figure 4.1.

We call an OSR transition from the *base* version to more optimized code (such as opt_1 in Figure 4.1) an *Optimize OSR*. The OSR support in the Java HotSpot server compiler [PVC01] uses this kind of transition.

Some virtual machines allow an OSR transition from optimized code such as opt_1 in Figure 4.1 to unoptimized code (the *base* version). We call this a *Deoptimize OSR* transition. This was the original OSR transition pioneered by Hölzle et al. [HCU92] to allow online debugging of optimized code in the SELF [CU91] virtual machine.

Systems such as the Jikes RVM [AAB+05], V8 VM [6], and JavaScriptCore [7] support both *Optimize OSR* and *Deoptimize OSR* transitions. Once a system has deoptimized back to the base code, it can potentially trigger another *Optimize OSR*, perhaps at a higher-level of optimization.

We call a transition from optimized code such as opt_1 to more optimized code such as opt_2 in Figure 4.1 a *Reoptimize OSR*. Further, we call an OSR transition from more

6. https://developers.google.com/v8/
7. http://trac.webkit.org/wiki/JavaScriptCore/

optimized code (e.g., opt_2) to the last version of less optimized code (e.g., opt_1) a *Last-version OSR.*

The OSR technique presented in this chapter supports both OSR transitions to a more optimized version and deoptimizations to the last version. Thus, if one starts with the base code, our OSR machinery can be used to perform an *Optimize OSR* transition. From that state, our OSR machinery can be used either as a *Deoptimize OSR* transition to return to the base code (which is the last version of the code), or as a *Reoptimize OSR* to transition to an even more optimized version. Our OSR implementation always caches the last version of the code, so it can also be used to support a *Last-version OSR* to transition from a higher-level of optimization to the previous level.

We now present the API of our OSR implementation [8].

4.2 The OSR API

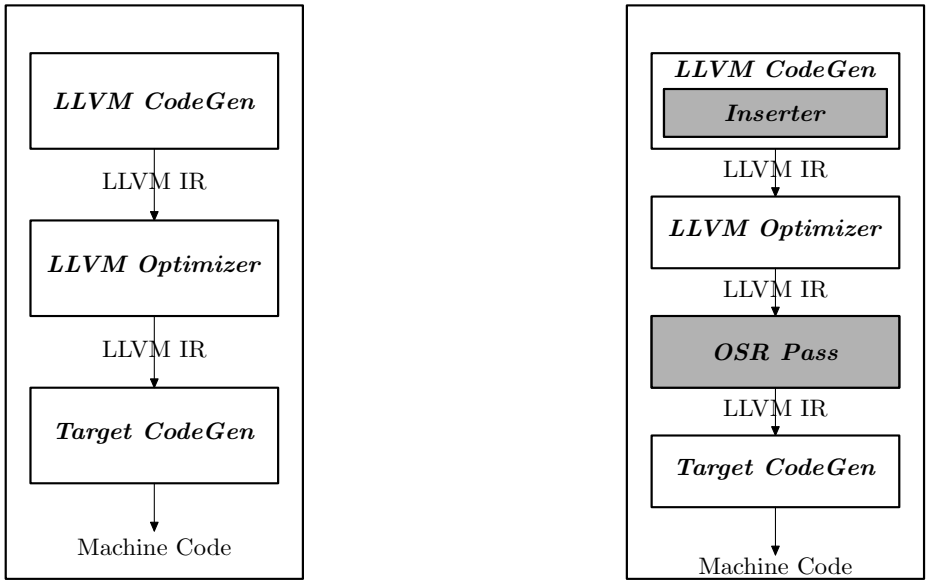
The key objective of this work was to build a modular system with a clean interface that is easy to use for VM and JIT compiler writers. In this section, we present the API of our OSR module and how JIT compiler developers who are already building JITs/VMs with LLVM can use our module to add OSR functionality to their existing JITs. We provide some concrete examples, based on our McJIT implementation of OSR-based dynamic inlining.

Figure 4.2(a) represents the structure of a typical JIT developed using LLVM. *LLVM CodeGen* is the front-end that produces LLVM IR for the JIT. The JIT compiler may perform transformations on the IR via the *LLVM Optimizer*. This is typically a collection of transformation and optimization passes that are run on the LLVM IR. The output (i.e., the transformed LLVM IR) from the optimizer is passed to the target code generator, *Target CodeGen*, that produces the appropriate machine code for the code in LLVM IR.

In Figure 4.2(b), we show a JIT (such as that shown in Figure 4.2(a)) that has been retrofitted with OSR support components (the shaded components). We describe the functions of *Inserter* and *OSR Pass* shown in Figure 4.2(b) shortly. In Section 4.3, we present

8. Available at http://www.sable.mcgill.ca/mclab/mcosr/

the implementation of these components and how they interact with the JIT to provide OSR support to the JIT.



(a) Existing JIT (b) Retrofitted JIT

Figure 4.2 – Retrofitting an existing JIT with OSR support.

4.2.1 Adding the OSR Point Inserter

To support OSR, a JIT compiler must be able to mark the program points (henceforth called OSR points) where a running program may trigger OSR. A developer can add this capability to an existing JIT by modifying the compiler to call the *genOSRSignal* function, provided by our API, to insert an OSR point at the beginning of a loop during the LLVM code generation of the loop. The LLVM IR is in SSA form. As will be shown later, an OSR point instruction must be inserted into its own basic block, which must be preceded by the loop header block containing all the ϕ nodes. This ensures that if OSR occurs at run time, the continuation block can be efficiently determined.

In addition to marking the spot of an OSR point, the JIT compiler writer will want to indicate what transformation should occur if that OSR point triggers at run time. Thus, the *genOSRSignal* function requires an argument which is a pointer to a *code transformer*

function - i.e. the function that will perform the required transformation at run time when an OSR is triggered. A JIT developer that desires different transformations at different OSR points can simply define multiple code transformers, and then insert OSR points with the desired transformation for each point. A valid transformer is a function pointer of the type *Transformer* that takes two arguments as shown below.

```
typedef unsigned int OSRLabel;
typedef bool (*Transformer) (llvm::Function*, OSRLabel);
```

The first argument is a pointer to the function to be transformed. The second argument is an unsigned integer representing the label of the OSR point that triggered the current OSR event. The code of the transformer is executed if the executing function triggers an OSR event at a corresponding label. A user may specify a *null* transformer if no transformation is required. [9] As an example of a transformation, our OSR-based dynamic inliner (Section 5.1) uses the transformer shown in Listing 4.1. It inlines all call sites annotated with label *osrPt*.

After the inliner finishes, the OSR pass is executed over the new version of the function to process, any remaining OSR points. Finally, as shown in lines 13 – 18 of the figure, some LLVM optimization passes are run on the new version of the function.

9. A *null* transformer can be used to test that the OSR triggering condition has been set up properly.

Listing 4.1 – A code transformer.

```
1  bool inlineAnnotatedCallSites (llvm::Function *F, osr::OSRLabel osrPt) {
2    ...
3    llvm::McJITInliner inliner (FIM, osrPt, TD);
4    inliner.addFunction( inlineVersion );
5    inliner. inlineFunctions ();
6    ...
7    // create and run the OSR Pass
8    llvm::FunctionPassManager FPM(M);
9    FPM.add(createOSRInfoPass());
10   FPM.run(*runningVersion);
11
12   // create and run LLVM optimization passes
13   llvm::FunctionPassManager OP(M);
14   OP.add(llvm::createCFGSimplificationPass ());
15   OP.add(llvm::ConstantPropagationPass ());
16   ...
17   OP.run(*runningVersion); ...
18 }
```

To illustrate with a concrete example of inserting OSR points, our OSR-based dynamic inlining implementation uses the code snippet shown in Listing 4.2 to insert conditional OSR points after generating the loop header block containing only ϕ nodes. In the code snippet (lines 6 – 12), a new basic block *osr* is created and the call to *genOSRSignal* inserts an OSR point into the block. The rest of the code inserts a conditional branch instruction into *target* and completes the generation of the LLVM IR for the loop.

Listing 4.2 – Sample code for inserting an OSR point.

```
1
2  ...
3  //  get  the  loop  header  block  ---  the target
4  llvm::BasicBlock* target  =  builder.GetInsertBlock();
5  llvm::Function* F  =  target->getParent();
6  //  create  the  osr  instruction  block
7  llvm::BasicBlock* osrBB =
8   llvm::BasicBlock::Create(F->getContext(), "osr", F);
9  //  now create  an  osr  pt  and  register  a  transformer
10 llvm::  Instruction * marker =
11     osr::Osr::genOSRSignal(osrBB,
12                     inlineAnnotatedCallSites ,
13                     loopInitializationBB  );
14  ...
15 //  create  the  osr  condition  instruction
16 llvm::Value *osrCond =  builder.CreateICmpUGT(counter,
17              getThreshold(context ),  "ocond");
18  builder.CreateCondBr(osrCond, osrBB,  fallThru );
19  ...
```

4.2.2 Adding the OSR Transformation Pass

After modifying the JIT with the capability to insert OSR points, the next step is to add the creation and running of the OSR transformation pass. When the OSR pass is run on a function with OSR points, the pass automatically instruments the function by adding the OSR machinery code at all the OSR points (note that the JIT-compiler developer only has to invoke the OSR pass, the pass itself is provided by our OSR module).

The OSR pass is derived from the LLVM function pass. Listing 4.3 shows a simplified interface of the pass. An LLVM front-end, that is, an LLVM code generator, can use the following code snippet to create and run the OSR pass on a function F after the original LLVM optimizer in Figure 4.2(b) finishes.

```
llvm::FunctionPass* OIP = osr::createOSRInfoPass();
OIP->runOnFunction(*F);
```

The OSR pass can also be added to an LLVM function pass manager.

Listing 4.3 – The OSR Pass interface.

```
namespace osr {
  class OSRInfoPass : public llvm::FunctionPass {
  public:
    OSRInfoPass();
     virtual bool runOnFunction(llvm::Function& F);
     virtual const char* getPassName() const
    { return "OSR Info Collection Pass";} ...
  };
  llvm::FunctionPass* createOSRInfoPass();
}
```

4.2.3 Initialization and Finalization

To configure the OSR subsystem during the JIT's start-up time, the JIT developer must add a call to the method Osr::init. This method initializes the data structures and registers the functions used later by the OSR subsystem. The JIT developer must also add a call to the method **void** Osr:releaseMemory() to de-allocate the memory allocated by the OSR system. The code snippet in Listing 4.4 shows how an existing JIT can initialize and release the memory used by the OSR subsystem. As shown in line 4, the arguments to Osr::init are a JIT execution engine and the module. The execution engine and the module are used to register the functions used by the system.

Listing 4.4 – Initialization and Finalization in the JIT's *main* function.

```
int main(int argc, const char** argv) {
  ...
  // initialize the OSR data structures ...
  Osr::init(EE, module);

  ... // JIT's Code

  // free up the memory used for OSR ...
  Osr::releaseMemory();
  ...
  return 0;
}
```

4.3 Implementation

In the previous section, we outlined our API which provides a simple and modular approach to adding OSR support to LLVM-based JIT compilers. In this section, we present our implementation of the API. Our implementation assumes that the application is single-threaded. We first discuss the main challenges that influenced our implementation decisions, and our solution to those challenges.

4.3.1 Implementation Challenges

Our first challenge was how to mark OSR points. Ideally, we needed an instruction to represent an OSR point in a function. However, adding a new instruction to LLVM is a non-trivial process and requires rebuilding the entire LLVM system. It will also require users of our OSR module to recompile their existing LLVM installations. Hence, we decided to use the existing call instruction to mark an OSR point. This also gives us some flexibility as the signature of the called function can change without the need to rebuild any LLVM library.

A related challenge was to identify at which program points OSR instructions should be allowed. We decided that the beginning of loop bodies were ideal points because we could ensure that the control flow and phi-nodes in the IR could be correctly patched in a way that does not disrupt other optimization phases in LLVM.

The next issue that we considered was portability. We decided to implement at the LLVM IR, rather than at a lower level, for portability. This is similar to the approach used in Jikes research VM [FQ03], which uses byte-code, rather than machine code to represent the transformed code. This approach also fits well with the extensible LLVM pass manager framework.

A very LLVM-specific challenge was to ensure that the code of the new version is accessible at the old address without recompiling all the callers of the function. Finding a solution to this was really a key point in getting an efficient and local solution.

Finally, when performing an OSR, we need to save the current state (i.e., the set of live values) of an executing function and restore the same state later. Thus, the challenge is

how to restore values while at the same time keeping the SSA-form CFG of the function consistent.

We now explain our approach which addresses all these challenges. In particular, we describe the implementation of *Inserter* and *OSR Pass* shown in Figure 4.2(b).

4.3.2 OSR Point

In Section 4.2.1, we explained how a developer can add the capability to insert OSR points to an existing JIT. Here we describe the representation of OSR points.

We represent an OSR point with a call to a native function named *@__osrSignal*. It has the following signature.

```
declare void @__osrSignal(i8*, i64)
```

The first formal parameter is a pointer to some memory location. A corresponding argument is a pointer to the function containing the call instruction. This is used to simplify the integration of inlining; we discuss this in detail in Section 4.3.5. The second formal parameter is an unsigned integer. A function may have multiple OSR points; the integer uniquely identifies an OSR point.

The OSR module maintains a table named OSR function table (*oft*). The table maps a function in LLVM IR onto a set of OSR-point entries. The set can grow or shrink dynamically as new OSR points are added (e.g., after a dynamic inlining) and old OSR points removed (e.g., after an OSR). An entry e in the set is an ordered pair.

e = (*osr_call_inst*, *code_transformer*)

The first member of the pair — *osr_call_inst* — is the call instruction that marks the position of an OSR point in a basic block. The second is the *code_transformer* (Section 4.2.1).

4.3.3 The OSR Pass

The OSR pass in Figure 4.2(b) is a key component of our OSR implementation. As shown in Listing 4.3, the OSR transformation pass is derived from the LLVM *FunctionPass* type. Like all LLVM function passes, the OSR pass runs on a function via its *runOnFunction* (Listing 4.3) method.

The pass first inspects a function's *oft* entry to determine whether the function has at least one OSR point. It returns immediately if the function has no OSR points. Otherwise, it instruments the function at each OSR point. Figure 4.3 shows a simplified CFG of a loop with no OSR points. The basic block labelled *LH1* is the loop header. *LB* contains the code for the body of the loop; and the loop exits at *LE*.

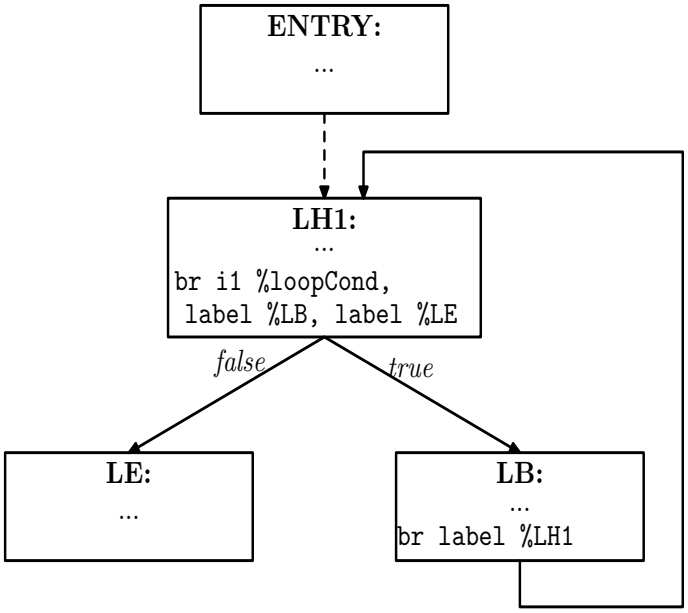


Figure 4.3 – A CFG of a loop with no OSR points.

Figure 4.4 shows a simplified CFG for the loop in Figure 4.3 with an OSR point. This represents typical code an LLVM front-end will generate with OSR enabled. Insertion of OSR points is performed by *Inserter* shown in Figure 4.2(b). The loop header block (now *LH0* in the Figure 4.4) terminates with a conditional branch instruction that evaluates the Boolean flag *%osrCond* and branches to either the basic block labelled *OSR* or to *LH1*. *LH1* contains the loop termination condition instruction. *LB* contains the code for the body of the loop; the loop exits at *LE*.

The OSR compilation pass performs a liveness analysis on the SSA-form CFG to determine the set of live variables at a loop header such as *LH0* in Figure 4.4. It creates, using the LLVM cloning support, a copy of the function named the *control version*. As we explain later in this section, this is used to support the transition from one version of the function

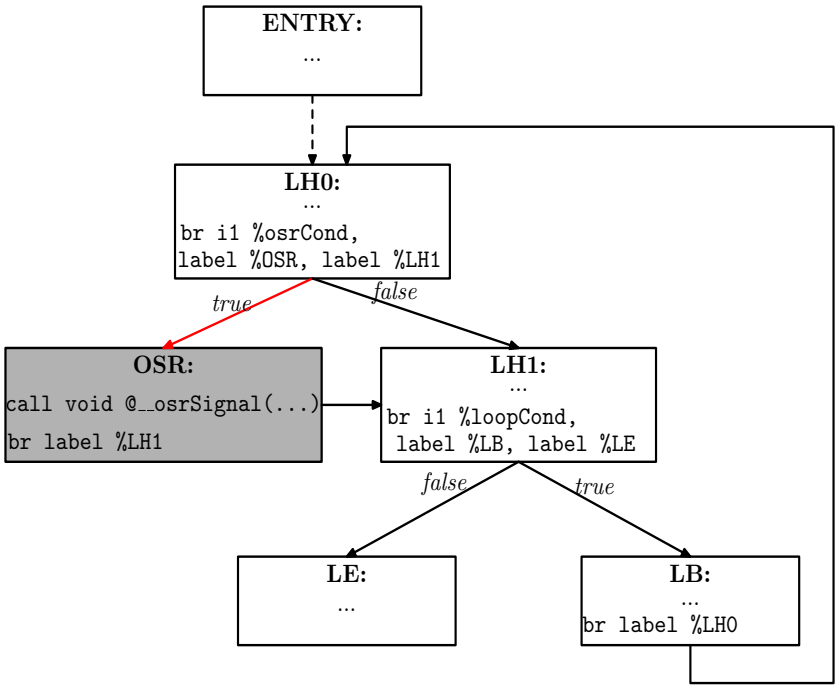


Figure 4.4 – The CFG of the loop in Figure 4.3 after inserting an OSR point.

to another at run time. It also creates a descriptor [HCU92, FQ03] for the function. The descriptor contains useful information for reconstructing the state of a function during an OSR event. In our approach, a descriptor is composed of:

- a pointer to the current version of the function;
- a pointer to the control version of the function;
- a map of variables from the original version of the function onto those in the control version; and
- the sets of the live variables collected at all OSR points.

After running the OSR pass on the loop shown in Figure 4.4, the CFG will be transformed into that shown in Figure 4.5. Notice that in the transformed CFG, the OSR block now contains the code to save the runtime values of the live variables and terminates with a return statement. We now describe in detail the kinds of instrumentation added to an OSR block.

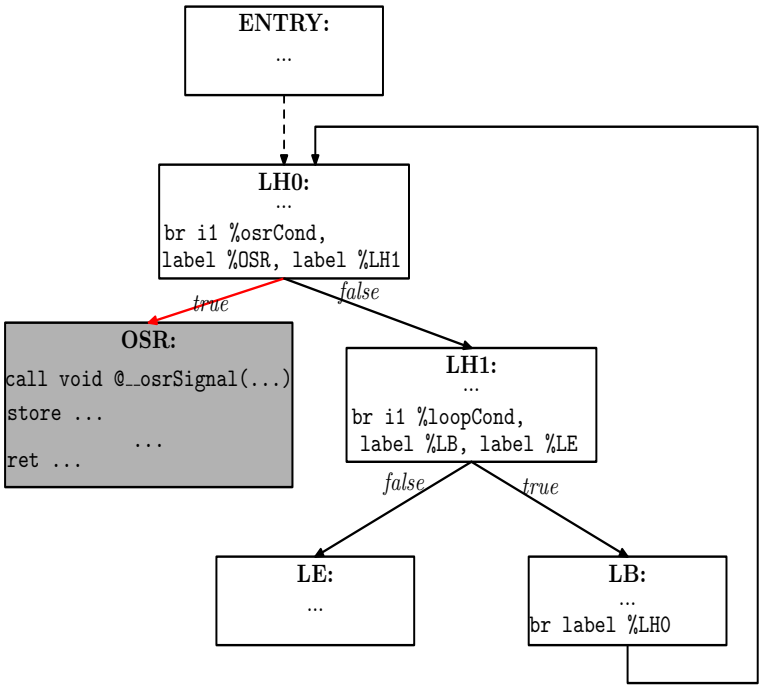


Figure 4.5 – The transformed CFG of the loop in Figure 4.4 after running the OSR Pass.

4.3.3.1 Saving Live Values

To ensure that an executing function remains in a consistent state after a transition from the running version to a new version, we must save the current state of the executing function. This means that we need to determine the live variables at all OSR points where an OSR transition may be triggered. Dead variables are not useful.

As highlighted in Section 4.2, we require that the header of a loop with an OSR point always terminates with a conditional branch instruction of the form:

```
br i1 %et, label %osr, label %cont
```

This instruction tests whether the function should perform OSR. If the test succeeds (i.e., *%et* is set to ***true***), the succeeding block beginning at label *%osr* will be executed and OSR transition will begin. However, if the test fails, execution will continue at the continuation block, *%cont*. This is the normal execution path.

In *%osr* block, we generate instructions for saving the runtime value of each live variable computed by the liveness analysis. The code snippet in Listing 4.5 shows a typical *osr* block in a simplified form.

Listing 4.5 – OSR instrumentation.

```
1
2 osr:
3    call  void @__osrSignal(f, i64  1)
4    store  double  %7, double* @live
5    store  double  %8, double* @live1
6    ...
7    store  i32  1,  i32* @osr_flag
8    call  void @__recompile(f, i32 1)
9    call  void @f (...)
10   call  void @__recompileOpt(f)
11   ret  void
```

The call to *@__osrSignal(f, i64 1)* in line 2 marks the beginning of the block. Following this call is a sequence of ***store*** instructions. Each instruction in the sequence saves the runtime value of a live variable into a global variable *@live**. The last ***store*** instruction stores the value 1 into *@osr_flag*. If *@osr_flag* is non-zero at run time, then the executing function is performing an OSR transition. We explain the functions of the instructions in lines 7 – 10 later.

The saved variables are mapped onto the variables in the control version. This is a key step as it allows us to correctly restore the state of the executing function during an OSR.

4.3.4 Restoration of State and Recompilation

The protocol used to signify that a function is transitioning from the executing version to a new version, typically, a more optimized version [10], is to set a global flag. The flag is reset after the transition.

At run time, the running function executes the code to save its current state. It then calls the compiler to recompile itself and, if a code *transformer* is present, the function is

10. It may also transition from an optimized version to a less optimized version depending on the application.

transformed before recompilation. The compiler retrieves the descriptor of the function and updates the running version using the *control* version as illustrated in Figure 4.6.

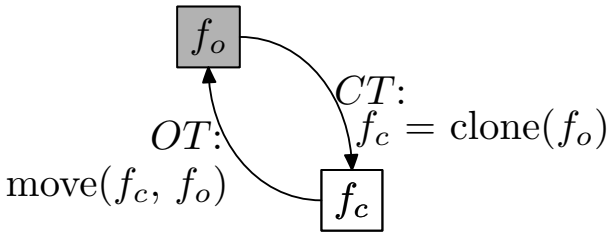


Figure 4.6 – State management cycle.

Let f_o denote the original version of the LLVM IR of the running function, and f_c denote the control version that was generated by cloning the original version. We denote the set of all the live variables of f_o at the program point p_o with $V_o(p_o)$. Similarly, $V_c(p_c)$ denotes the state of the control version at the matching program point p_c. Because f_c is a copy of f_o, it follows that

$V_o(p_o) \equiv V_c(p_c)$.

Figure 4.6 illustrates the state management cycle of the running function. The function starts with version f_o. At compilation time [11] (shown as event CT in Figure 4.6), we clone f_o to obtain f_c. We then compile f_o. At run time, when an OSR (event OT in Figure 4.6) is triggered by the running function, we first remove the instructions in f_o and then *move* the code (LLVM IR) of f_c into f_o, transform/optimize as indicated by the OSR transform, and then recompile f_o and execute the machine code of f_o.

This technique ensures that the machine code of the running function is always accessible at the same address. Hence, there is no need to recompile its callers: the machine code of the transformed f_o is immediately available to them at the old entry point of the running function.

To locate the continuation program point p_o ($p_o \equiv p_c$), the compiler recovers the OSR entry of the current OSR identifier; using the variable mappings in the descriptor, finds the instruction that corresponds to the current OSR point. From this, it determines the basic

11. This includes the original compilation and all subsequent recompilations due to OSR.

block of the instruction. Because the basic block of an OSR point instruction has one and only one predecessor, the compiler determines the required target, p_o.

4.3.4.1 Restoration of State

To restore the state of the executing function, we create a new basic block named *prolog* and generate instructions to load all the saved values in this block; we then create another basic block that merges a new variable defined in the *prolog* with that entering the loop via the loop's entry edge. We ensure that a loop header has only two predecessors and because LLVM IR is in SSA form, the new block consists of ϕ nodes with two incoming edges: one from the initial loop's entry edge and the other from *prolog*. The ϕ nodes defined in the merger block are used to update the users of an instruction that corresponds to a saved live variable in the previous version of the function.

Figure 4.7 shows a typical CFG of a running function before inserting the code for recovering the state of the function. The basic block *LH1* defines a ϕ node for an induction variable ($\%i$ in Figure 4.7) of a loop in the function. The body of the loop, *LB*, contains a ***add*** instruction that increments the value of $\%i$ by 1.

Assuming that we are recovering the value of $\%i$ from the global variable $@live\_i$, Figure 4.8 shows the CFG after inserting the blocks for restoring the runtime value of $\%i$. In this figure, *prolog* contains the instruction that will load the runtime value of $\%i$ from the global variable $@live\_i$ into $\%\_i$; similarly, the basic block *prolog.exit* contains a ϕ instruction ($\%\_m\_i$) that merges $\%\_i$ from *prolog* and the value 1 from *ENTRY*. This variable (i.e., $\%\_m\_i$) replaces the incoming value (1) from *ENTRY* in the definition of $\%i$ in the loop header (*LH1*) as shown in Figure 4.8. Notice that the incoming block *ENTRY* has been replaced with *prolog.exit* (*PE*) in the definition of $\%i$ in *LH1*.

Fixing the CFG to keep the SSA form consistent is non-trivial. A simple replacement of a variable with a new variable does not work. Only variables dominated by the definitions in the merger block need to be replaced. New ϕ nodes might be needed at some nodes with multiple incoming edges (i.e., only those that are in the dominance frontier of the merger block). Fortunately, the LLVM framework provides an SSA Updater that can be used to update the SSA-form CFG. We exploited the SSA Updater to fix the CFG.

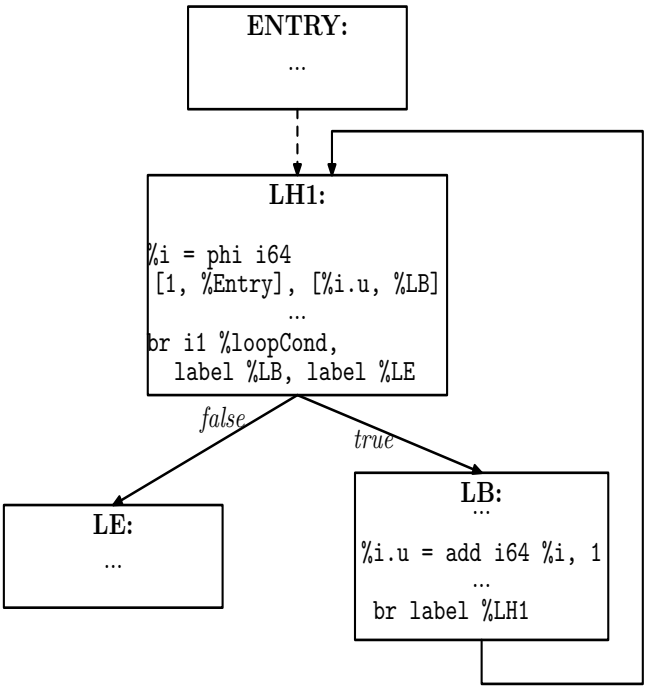


Figure 4.7 – A CFG of a loop of a running function before inserting the blocks for state recovery.

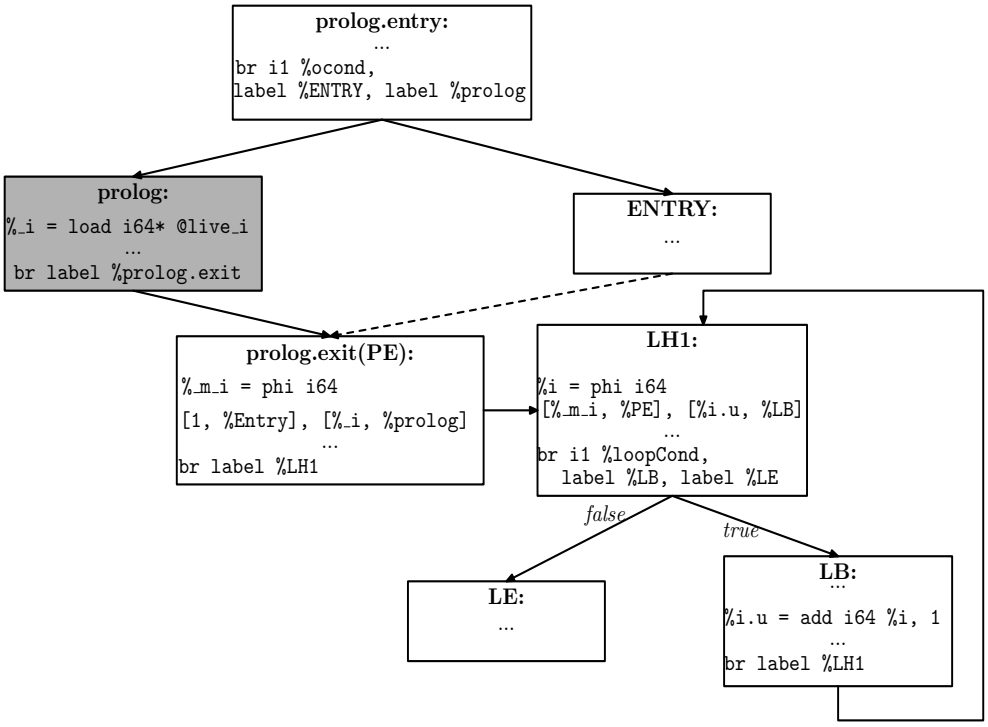


Figure 4.8 – The CFG of the loop represented by Figure 4.7 after inserting the state recovery blocks.

To complete the state restoration process, we must fix the control flow to ensure that the function continues at the correct program point. For this, we insert a new entry block named *prolog.entry* that loads *@osr_flag* and tests the loaded value for zero to determine, during execution, whether the function is completing an osr transition or its being called following a recent completion of an OSR. The content of the new entry block is shown in the following code snippet.

```
1 prolog.entry:
2   %osrPt = load i32* @osr_flag
3   %cond = icmp eq i32 %osrPt, 0
4   br i1 %cond, label %entry, label %prolog
```

If $\%osrPt$ is non-zero, the test succeeds and the function is completing an OSR; it will branch to $\%prolog$. In $\%prolog$, all the live values will be restored and control will pass to the target block: the loop header where execution will continue. However, if $\%osrPt$ is zero, the function is not currently making a transition: it is being called anew. It will branch to the original entry basic block, where its execution will continue.

As shown in Figure 4.8, the basic block *prolog.entry* terminates with a conditional branch instruction. The new version of the running function will begin its execution from *prolog.entry*. After executing the block, it will continue at either *prolog* or *ENTRY* (the original entry block of the function) depending on the runtime value of *%cond*.

4.3.4.2 Recompilation

We now return to the instructions in lines 7 – 10 of Listing 4.5. The instruction in line 7 calls the compiler to perform OSR and recompile f using the code transformer attached to OSR point 1. After that, function f will call itself (as shown in line 8), but this will execute the machine code generated for its new version. This works because the LLVM recompilation subsystem replaces the instruction at the entry point of function f with a jump to the entry point of the new version. During this call, the function completes OSR and resumes execution. The original call will eventually return to the caller any return value returned by the recursive call.

Normally after an OSR, subsequent calls (if any) of f executes the code in the *prolog.entry*, which tests whether or not the function is currently performing an OSR. However, this test succeeds only during an OSR transition; in other words, the execution of the code in *prolog.entry* after an OSR has been completed is redundant. To optimize away the *prolog.entry*, we again call the compiler (line 9 in Listing 4.5) but this time, the compiler only removes the *prolog.entry* and consequently, other dead blocks, and recompile f. In Section 5.3.2, we compare the performance of our benchmarks when the *prolog.entry* is eliminated with the performance of the same benchmarks when the *prolog.entry* is not eliminated.

4.3.5 Inlining Support

Earlier, we discussed the implementation of OSR points and how the OSR transformation pass handles OSR points. However, we did not specify how we handled OSR points inserted into a function from an inlined call site. A seamless integration of inlining optimization poses further challenges. When an OSR event is triggered at run time, the runtime system must retrieve the code transformer attached to the OSR point from the *oft* entry of the running function. How then does the system know the original function that defined an inlined OSR point? Here we explain how our approach handles inlining.

Remember that an OSR point instruction is a call to a function. The first argument is a pointer to the enclosing function. Therefore, when an OSR point is inlined from another function, the first argument to the inlined OSR point (i.e., a call instruction) is a function pointer to the inlined function. From this, we can recover the *transformer* associated with this point by inspecting *oft* using this pointer. We can then modify these OSR points by changing the first argument into a pointer to the current function and assign a new ID to each inlined OSR point. We must also update the *oft* entry of the caller to reflect these changes.

We distinguish two inlining strategies: static and dynamic. In static inlining, a call site is expanded before executing the *caller*. This expansion may introduce a new OSR point from the *callee* into the caller and invalidates all the state information collected for the existing OSR points. We regenerate this information after any inlining process.

Dynamic inlining concerns inlining of call sites in a running function during the execution of the function after observing, for some time, its runtime behaviour. Typically, we profile a program to determine *hot* call sites and inline those subject to some heuristics. We used OSR support to implement dynamic inlining of call sites in long-running loops. We discuss this implementation in the next chapter.

4.4 Summary

In this chapter, we have introduced a modular approach to implementing OSR for LLVM-based JIT compilers. Our approach should be very easy for others to adopt because it is based on the LLVM and is implemented as an LLVM pass. Furthermore, we found a solution which does not require any special data structures for storing stack frame values, nor any instrumentation in the callers of functions containing OSR points. It also does not introduce any changes to LLVM which would require rebuilding the LLVM system. Finally, our approach also provides a solution for the case where a function body containing OSR points is inlined, in a way that maintains the OSR points and adapts them to the inlined context.

In the next chapter, we describe a case study of how we have used our OSR implementation to support selective dynamic inlining of hot call sites in long-running loops in the McVM JIT compiler for the MATLAB language. Then we describe and discuss the experiments that we conducted to measure the overheads OSR and the benefits of our OSR-supported selective dynamic inlining.

Chapter 5
Selective Dynamic Inlining in McVM

This chapter is a continuation of the previous chapter, which is about the implementation of our OSR approach. Here, we present an example application of the OSR approach to support selective dynamic inlining in McJIT. We selected this as our first application of OSR because inlining impacts OSR since it must properly deal with OSR points in the inlined functions. Moreover, inlining can provide larger scope for many traditional compiler optimizations and can increase the opportunity for loop vectorization.

The main contributions of this chapter are

Using OSR in McJIT for selective dynamic inlining: In order to demonstrate the effectiveness of our OSR module, we have implemented an OSR-based dynamic inliner that will inline function calls within dynamically hot loop bodies. This has been completely implemented in McVM/McJIT.

Experimental measurements of overheads/benefits: We have performed a variety of measurements on a set of 16 MATLAB benchmarks. We have measured the overheads of OSRs and selective dynamic inlining. This shows that the overheads are usually acceptable and that dynamic inlining can result in performance improvements.

5.1 The McJIT dynamic inliner

In our approach to dynamic inlining, we first modified McJIT to identify potential inlining candidates. In our case, a call is considered an inlining candidate if the body of the called function is less than 20 basic blocks, or it is less than 50 basic blocks and it has an interpreter environment associated with the body. [1] McJIT generates LLVM IR for each function in a program. The LLVM IR generated by McJIT may contain calls to the interpreter for special cases and for those cases the symbol environment set-up code facilitates the interaction with the interpreter. In our case, inlining can reduce the interpreter environment overheads.

We then modified McJIT so that loops which contain potential inlining candidates are instrumented with a hotness counter and a conditional which contains an OSR point (where the OSR point is associated with a new McJIT inlining transformer). When an OSR triggers (i.e. the hotness counter reaches a threshold), the McJIT inlining transformation will inline all potential inlining candidates associated with that OSR point.

There are many strategies for determining which loops should be given an OSR point, and a JIT developer can define any strategy that is suitable for his/her situation. For McJIT, we defined two such general strategies, as follows:

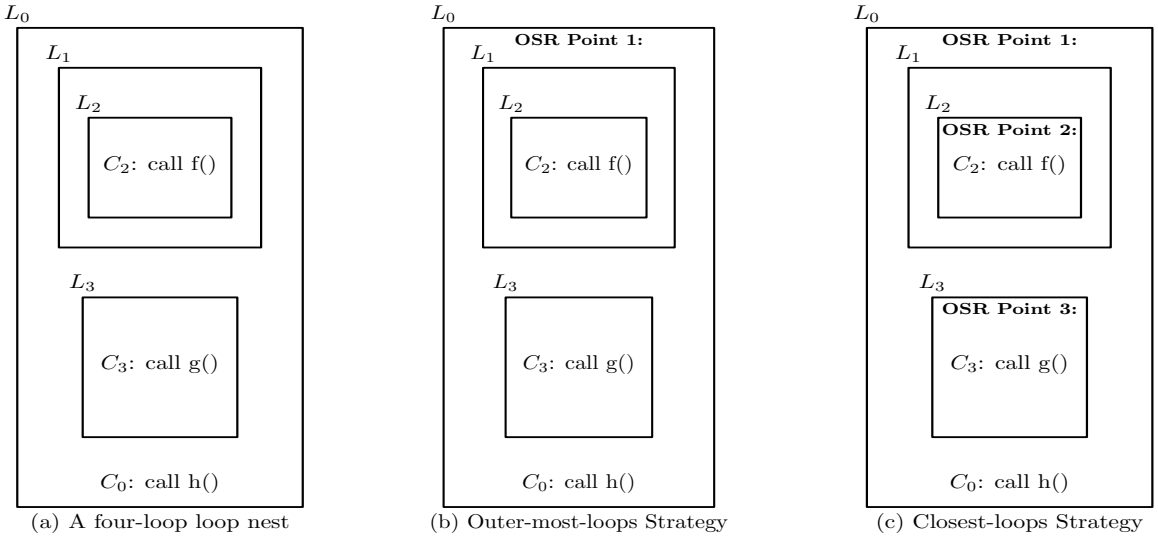
CLOSEST Strategy: The LLVM front-end is expected to insert OSR points only in the loop that is closest to the region that is being considered for optimization. For example, to implement a dynamic inlining optimization using this strategy, an OSR point is inserted at the beginning of the closest loop enclosing an interesting call site. This strategy is useful for triggering an OSR as early as possible, i.e., as soon as that closest enclosing loop becomes hot.

OUTER Strategy: The LLVM front-end is expected to insert an OSR point at the beginning of the body of the outer-most loop of a loop nest containing the region of interest. This approach is particularly useful for triggering many optimizations in a loop nest with a single OSR event. In the case of dynamic inlining, one OSR will trigger inlining of all inlining candidates within the loop nest. The potential drawback

1. We experimented with different thresholds for basic blocks but found 20 and 50 to work best for our benchmarks.

of this strategy is that the OSR will not trigger until the outermost loop becomes hot, thus potentially delaying an optimization.

In Figure 5.1, we illustrate the difference between the two strategies using an hypothetical loop nest. We use a call site to represent an interesting region for optimization.



(a) A four-loop loop nest (b) Outer-most-loops Strategy (c) Closest-loops Strategy

Figure 5.1 – A loop nest showing the placement of OSR points using the closest or outermost strategy.

A loop is represented with a box. The box labelled L_0 denotes the outer-most loop of the loop nest. The nest contains four loops and has a depth of 3. Loops L_1 and L_3 are at the same nesting level. L_2 is nested inside L_1. The loop nest has three call sites: C_0 in loop L_0, C_2 in loop L_2, and C_3 in loop L_3. Figure 5.1(a) shows the loop nest with no OSR points.

With the outer-most-loops strategy, an OSR point will be inserted only at the beginning of the outer-most loop, L_0 as shown in Figure 5.1(b). However, if the strategy is closest-enclosing loops, the front-end will insert an OSR point at the beginning of loops L_0, L_2, and L_3 as shown in Figure 5.1(c). Although C_2 is inside L_1, no OSR points are inserted into L_1 because L_1 is not the closest-enclosing loop of C_2.

As shown in the figure, the outer-most-loops strategy causes only one OSR point to be inserted into the entire loop nest, while the closest-enclosing-loops strategy causes three

OSR points to be inserted. Thus, depending on the optimization performed during an OSR event, the choice of strategy can make a difference in performance.

In our VM, a user specifies an OSR strategy from the command line when invoking the VM, like the following example.

```
./mcvm -jit_enable true -jit_osr_enable true
       -jit_osr_strategy outer.
```

This command starts McVM with OSR enabled with *outer* strategy. In our JIT, the default strategy is *outer*.

When the OSR triggers it calls the McJIT inliner transformation. Our McJIT inliner calls the LLVM basic-inliner library to do the actual inlining. However, the McJIT inliner must also do some extra work because it must inline the correct version of *callee* function body. The key point is that if the *callee* has an OSR point, it must not inline the version of the callee which has already been instrumented with the code to store values of the live variables at this OSR point. If this version is inlined into the *caller* — the function that is performing OSR— the instrumentation becomes invalid as the code does not correctly save the state of the caller at that inlined OSR point. We resolved this problem by recovering the *control* version of the called function (*callee*) and modifying the call site. We change the function called by the call instruction to the control version of the callee. For instance, if the inlined call site is **`call void`** `@f(...)`, and the control version of f is f', then the call site will be changed to **`call void`** `@f'(...)`. Note that the control version has an identical OSR point but is not instrumented to save the runtime values of live variables at that program point. For consistency, the function descriptor of the function is updated after inlining as outlined in Section 4.3.5.

5.2 Symbol Environment Simplification

One important optimization that we perform on an inlined code region is the symbol environment optimization. As discussed in Section 2.2.3, the code of a function can contain calls to the interpreter. Some calls to the interpreter require the function's symbol environment, and a function that contains such calls has symbol environment initialization code in

its entry basic block. If a function with a symbol environment is frequently called within a hot loop body, the execution of the symbol environment set-up code can be a major source of overhead, especially if multiple functions with symbol set-up code have been inlined into a function.

Inlining, however, enables an opportunity to eliminate the symbol set-up code from an inlined code region. If the calling function has a symbol environment set-up in its entry block, this symbol environment can be used by the code in the inlined region. This will render the symbol set-up code from an inlined function redundant. The code can then be removed from the inlined region.

As an example, Listing 5.1 shows the inner loop of the *sim_anl* [mat13] MATLAB program.

Listing 5.1 – The inner loop of *sim_anl*.

```
1  for k=0:500
2          %We generate new test point using mu_inv function [3]
3          dx=mu_inv(2*rand(size(x))-1,mu).*(u-l);
4          x1=x+dx;
5          x1=(x1 < l).* l+(l <= x1).*(x1 <= u).*x1+(u < x1).*u;
6          fx1=feval(f,x1);df=fx1-fx;
7
8          if (df < 0 || rand < exp(-T*df/(abs(fx)+eps)/TolFun))==1
9              x=x1;fx=fx1;
10         end
11
12         if fx1 < f0 ==1
13             x0=x1;f0=fx1;
14         end
15 end
```

The entry basic block of the LLVM code generated by McJIT for *sim_anl* contains the instructions shown in Listing 5.2. Instructions 5 and 7 set up a symbol environment for function *sim_anl*.

Listing 5.2 – LLVM code for *sim_anl* entry basic block. (We show only the most relevant instructions.)

```
1 define void @sim_anl_0x1f86a80({ i8*, i8*, i8*, i8*, i64, double, i64 }* %arg,
2 { i8*, i8*, i64 }* %arg1) {
3 entry:
4   ...
5   %tmp13 = call i8* @''ProgFunction::getLocalEnv''
6                     (i8* inttoptr (i64 30596480 to i8*))
7   %env = call i8* @''Environment::extend''(i8* %tmp13)
8   ...
```

Line 3 of Listing 5.1 contains a call to function mu_inv. The MATLAB code, and the corresponding LLVM code generated by McJIT for mu_inv is shown in Listing 5.3 and Listing 5.4 respectively.

Listing 5.3 – Function *mu_inv*.

```
1 function x=mu_inv(y,mu)
2 %This function is used to generate new point according to lower and
3 %upper %and a random factor proportional to current point.
4   x=(((1+mu).^abs(y)-1)/mu).*sign(y);
5 end
```

Listing 5.4 – McJIT generated LLVM code for *mu_inv*.

```
1  define void @mu_inv_0x1f869a0({ i8*, double, i64 }* %arg, { i8*, i64 }* %arg1) {
2  entry:
3    ...
4    %tmp5 = call i8* @''ProgFunction::getLocalEnv''
5                     (i8* inttoptr (i64 30596288 to i8*))
6    %r_env = call i8* @''Environment::extend''(i8* %tmp5)
7    ...
8    br i1 %tmp11, label %bb29, label %bb
9  bb:                                               ; preds = %entry
10   %tmp12 = call i8* @''ArrayObj::getArrayObj''(i8* %tmp9, i64 0)
11   %tmp13 = call i8* @''Environment::bind''(i8* %r_env,
12                    i8* inttoptr (i64 30559968 to i8*), i8* %tmp12)
13
14   %tmp14 = call i8* @''MatrixF64Obj::makeScalar''(double %tmp7)
15   %tmp15 = call i8* @''Environment::bind''(i8* %r_env,
16                    i8* inttoptr (i64 30560032 to i8*), i8* %tmp14)
17
18   %tmp16 = call i8* @''Interpreter::evalBinaryExpr''
19              (i8* inttoptr (i64 33888032 to i8*), i8* %r_env)
20   ...
21 ...
22 }
```

Notice that the LLVM code for function mu_inv (Listing 5.4) contains a symbol environment set-up code in lines 4 – 6; some uses of the symbol environment (i.e., LLVM virtual register **%r_env** created in line 6) for runtime variable binding in lines 11 and 15, and for evaluating an expression in line 18 – 19.

If our dynamic inliner decides to inline function mu_inv into function sim_anl, the inner loop of *sim_anl* shown in Listing 5.1 will contain the set up code and will be executed many times. Because function *sim_anl* also has a symbol environment associated with it (i.e., **%env** defined in Listing 5.2), it is possible to eliminate the symbol set up instructions in the inlined region corresponding to the code of mu_inv.

Thus, we use the algorithm in Algorithm 1 to eliminate symbol environment set-up code from an inlined region. The input to Algorithm 1 is a function in LLVM IR whose relevant call sites have just been inlined, and a set of basic blocks. Each basic block in the set is the beginning of an inlined region (the code of the called function at an inlined call site).

```
Input: LLVM IR, and a set of LLVM basic blocks
Output: A simplified LLVM IR
if caller has a symbol environment E then
    /* process each inlined region */
    for each inlined region R do
        if R has a symbol environment E_R then
            find all the uses of E_R in R ;
            for each use U of E_R do
                replace E_R with E;
            end
            remove the definition of E_R from R
        end
    end
end
```

Algorithm 1: Simplification of symbol environments.

The algorithm first checks whether there are inlined regions and searches the entry basic block of the input function (which we call the *caller*) to find the symbol environment associated with the function. If no symbol environment is found in the entry block, the algorithm terminates. If, however, the environment is found, the algorithm processes each code region found in the input set of basic blocks. It locates the symbol environment in the current code region and replaces all the uses of the symbol environment found in the region with the symbol environment of the caller. It then removes the set up code for the symbol environment in the code region.

In the next section, we discuss our experimental results, and the impact of this symbol environment simplification on performance.

5.3 Experimental Results

We used our McJIT dynamic inliner to study the overheads of OSR and the potential performance benefit of inlining. We used a collection of MATLAB benchmarks from a

previous MATLAB research project and other sources [RGG+96, Cle04, Pre86], Table 5.1 gives a short description of each benchmark. All the benchmarks have one or more loops, the table also lists the total number of loops and max loop depth for each benchmark.

BM	**Description**	**# Loops**	**Max Depth**
adpt	adaptive quadrature using Simpson's rule	4	2
capr	capacitance of a transmission line using finite difference and and Gauss-Seidel iteration.	10	2
clos	transitive closure of a directed graph	4	2
crni	Crank-Nicholson solution to the one dimensional heat equation	7	2
dich	Dirichlet solution to Laplace's equation	6	3
diff	Young's two-slit diffraction experiment	13	4
edit	computes the edit distance of two strings	7	2
fdtd	3D FDTD of a hexahedral cavity with conducting walls	1	1
fft	fast fourier transform	6	3
fiff	finite-difference solution to the wave equation	13	4
mbrt	Mandelbrot set	3	2
nb1d	N-body problem coded using 1d arrays for the displacement vectors	6	2
nfrc	computes a Newton fractal in the complex plane -2..2,-2i..2i	3	2
nnet	neural network learning AND/OR/XOR functions	11	3
schr	solves 2-D Schroedinger equation	1	1
sim	Minimizes a function with simulated annealing	2	2

Table 5.1 – The benchmarks.

The configuration of the computer used for the experimental work is:

Processor: Intel(R) Core(TM) i7-3930K CPU @ 3.20GHz
RAM: 16 GB;
Cache Memory: L1 32KB, L2 256KB, L3 12MB;
Operating System: Ubuntu 12.04 x86-64;
LLVM: version 3.0; and
McJIT: version 1.0.

Our main objectives were:

- To measure the overhead of OSR events on the benchmarks over the outer-most and closest-loop strategies. The overhead includes the cost of instrumentation and performing OSR transitions. We return to this in Section 5.3.1.
- To measure the impact of selective inlining on the benchmarks. We discuss this in detail in Section 5.3.2.

We show the results of our experiments in Table 5.2 and Table 5.3. For these experiments, we collected the execution times (shown as *t(s)* in the tables) measured in seconds, for 7 runs of each benchmark. To increase the reliability of our data, we discarded the highest and the lowest values and computed the average of the remaining 5 values. To measure the variation in the execution times, we computed the standard deviation (STD) (shown as *std*) of the 5 values for each benchmark under 3 different categories. All the results shown in both tables were collected using the outer-most-loops strategy, with the default LLVM code-generation optimization level.

The column labelled *Normal* gives the average execution times and the corresponding STDs of the benchmarks run with OSR disabled, while the column labelled *With OSR* gives similar data when OSR was enabled. Column *With OSR* in Table 5.3 shows the results obtained when dynamic inlining plus some optimizations enabled by inlining were on.

The number of OSR points instrumented at JIT compilation time is shown under *I* of the column labelled *#OSR*; while the number of OSR events triggered at run time is shown under the column labelled *T* of *#OSR*. The execution ratio for a benchmark is shown as the ratio of the average execution time when OSR was enabled to the average execution

	Normal(N)		**With OSR(O)**		**#OSR**		**Ratio**
BM	t(s)	std	t(s)	std	I	T	O/N
adpt	17.94	0.06	17.84	0.08	1	1	0.99
capr	11.61	0.01	11.63	0.02	2	2	1.00
clos	16.96	0.01	16.96	0.01	0	0	1.00
crni	7.20	0.04	7.40	0.04	1	1	1.03
dich	13.92	0.01	13.92	0.00	0	0	1.00
diff	12.73	0.07	12.80	0.09	0	0	1.01
edit	6.58	0.03	6.66	0.09	1	0	1.01
fdtd	12.14	0.03	12.16	0.05	0	0	1.00
fft	13.95	0.05	14.05	0.03	1	1	1.01
fiff	8.02	0.01	8.05	0.01	1	1	1.00
mbrt	9.05	0.11	9.22	0.11	1	1	1.02
nb1d	3.44	0.02	3.47	0.01	0	0	1.01
nfrc	9.68	0.05	10.00	0.04	2	2	1.03
nnet	5.41	0.02	5.59	0.03	2	1	1.03
schr	11.40	0.01	11.42	0.03	0	0	1.00
sim	15.26	0.03	15.92	0.07	1	1	1.04
GM							1.01

Table 5.2 – OSR Overhead.

	Normal(N)		**With OSR(O)**		**#OSR**				**Ratio**
BM	t(s)	std	t(s)	std	I	T	FI	CA	O/N
adpt	17.94	0.06	17.85	0.06	1	1	1	F	0.99
capr	11.61	0.01	11.69	0.02	2	2	2	T	1.01
clos	16.96	0.01	17.18	0.22	0	0	0	F	1.01
crni	7.2	0.04	6.73	0.24	1	1	1	T	**0.93**
dich	13.92	0.01	13.94	0.01	0	0	0	F	1.00
diff	12.73	0.07	12.74	0.04	0	0	0	F	1.00
edit	6.58	0.03	6.66	0.07	1	0	0	F	1.01
fdtd	12.14	0.03	12.13	0.03	0	0	0	F	1.00
fft	13.95	0.05	13.91	0.02	1	1	2	F	1.00
fiff	8.02	0.01	8.26	0.03	1	1	1	F	1.03
mbrt	9.05	0.11	9.06	0.03	1	1	1	F	1.00
nb1d	3.44	0.02	3.47	0.01	0	0	0	F	1.01
nfrc	9.68	0.05	4.26	0.02	2	2	5	T	**0.44**
nnet	5.41	0.02	5.71	0.03	2	1	1	F	1.05
schr	11.4	0.01	11.45	0.05	0	0	0	F	1.00
sim	15.26	0.03	14.72	0.09	1	1	1	F	**0.96**
GM									0.95

Table 5.3 – Dynamic inlining using OSR (lower execution ratio is better).

time when OSR was disabled (this is the default case). Columns *O/N* of Table 5.2 and *O/N* of Table 5.3 show, respectively, the ratio for each benchmark when OSR only was enabled and when OSR and inlining were enabled. The last row of Table 5.2 and Table 5.3 shows the average execution ratio (the geometric mean (GM)) over all the benchmarks. In Table 5.3, we show the number of functions inlined under *FI*. The column labelled *CA* indicates whether at least one function in the benchmark is called again after it has completed an OSR event.

The STDs of our data sets range from 0.00 to 0.24, showing that the execution times are quite reliable. We now discuss the results of our experiments in detail.

5.3.1 Cost of Code Instrumentation and OSR

Because our approach is based on code instrumentation, we wanted to measure the overhead of code instrumentation and triggering OSRs. This will allow us to assess the performance and develop an effective instrumentation strategy.

Column *O/N* of Table 5.2 shows that the overheads range from about 0 to 4%; this is also the range for the closest-enclosing-loops strategy, suggesting that the overheads under the two strategies are close. Out of the 16 benchmarks, 10 have at least one OSR point; and 8 of these 10 benchmarks triggered one or more OSR events. We have not shown the table of the results for the closest-enclosing loops because out of the 8 benchmarks that triggered an OSR event, the outer-most and the closest-enclosing loops are different only in 3 benchmarks: *mbrt*, *nfrc*, and *sim*. The execution ratios for these benchmarks under the closest-enclosing-loops strategy are: 1.00 for *mbrt*, 1.02 for *nfrc*, and 1.04 for *sim*. The *mbrt* and *nfrc* benchmarks have lower execution ratios under the closest-enclosing-loops strategy. It is not entirely clear whether the closest-enclosing-loops strategy is more effective than the outer-most-loops strategy; although, with these results, it appears that using the closest-loops strategy results in lower overheads. The choice between these two will depend largely on the kinds of the optimizing transformations expected at OSR points. We return to this discussion in Section 5.3.2, where we examine the effectiveness of our dynamic inlining optimization.

We investigated the space performance and found that, depending on the strategy, the three benchmarks (*mbrt*, *nfrc* and *sim*) compiled up to 3% more instructions under the closest-enclosing-loops strategy. This is hardly surprising; the OSR overhead depends on the number of OSR points instrumented and the number of OSR points triggered at run time. The size of the instrumentation code added at an OSR point in a function depends on the size of the live variables of the function at that point, and this varies depending on the position of the OSR point in a loop nest. The outer-most loop is likely to have the smallest set of live variables.

Although the overhead peaked at 4%, the average overhead over all the benchmarks (shown as *GM* in Table 5.2) is 1%. Thus, we conclude that on average, the overhead is reasonable and practical for computation-intensive applications. As we continue to develop effective optimizations for MATLAB programs, we will work on techniques to use OSR points in locations where subsequent optimizations are likely to offset this cost and therefore increase performance.

5.3.2 Effectiveness of Selective Inlining With OSR

Our objective here is to show that our approach can be used to support dynamic optimization. So, we measured the execution times of the benchmarks when dynamic inlining is enabled. When an OSR is triggered, we inline call sites in the corresponding loop nest. Column *With OSR* of Table 5.3 shows the results of this experiment.

The results show significant improvements for *crni*, *nfrc* and *sim*. This shows that our dynamic inlining is particularly effective for this class of programs. Further investigation revealed that these benchmarks inlined multiple small functions and several of these functions fall back to the McVM's interpreter to compute some complicated expressions. As discussed in Section 5.2, McJIT's interactions with the interpreter are facilitated by setting up a symbol environment for binding variables at run time. Our dynamic inlining enables the symbol environment simplfication discussed in Section 5.2, which eliminates the environment set-up instructions in the inlined code. This is the main cause of performance improvement in *nfrc* and *sim*, and is impossible to do without inlining.

Only the *fiff* and *nnet* show a real decrease in performance when using the outer-most-loop strategy with inlining. We found that the function inlined by *nnet* contains some expensive cell array operations, which our optimizer is currently unable to handle. The benchmark also triggered an OSR event once, but performed three OSR instrumentation phases: two at the compilation time and one re-instrumentation during the only OSR event.

We wanted to assess the impact of recompilation to optimize the *prolog.entry* block added during an OSR event; so we turned off recompilation after OSR and re-collected the execution times for the benchmarks. Out of the 9 benchmarks that performed inlining, only 3 benchmarks contain at least one further call to a function that completed an OSR. These are the rows with the value "*T*" against the column labelled *CA* in Table 5.3. The results for these benchmarks under the no-recompilation after OSR is: 1.01 for *capr*, 0.95 for *crni*, and 0.45 for *nfrc*. These results suggest that the recompilation to remove the *prolog.entry* contributes to the increase in performance for *capr* and *nfrc*. The basic block has the potential to disrupt LLVM optimizations and removing it might lead to better performance. The recompilation after OSR does not result in a slowdown for the other benchmarks.

In Section 5.3.1, we mentioned that the kinds of the optimizing transformations can guide the choice of strategy that lead to better performance. Considering the 3 benchmarks with a loop nest where the outer-most and closest-enclosing loops are different, that is, *mbrt*, *nfrc* and *sim*, we found that the outer-most-loop strategy outperforms the closest-enclosing-loop strategy. In particular, the *sim* benchmark results in about 5% performance degradation. These results support our claim.

We recorded the average performance improvement over all the benchmarks (shown as *GM* in Table 5.3) of 5%. We conclude that our OSR approach is effective, in that it efficiently supports this optimization, and that it works smoothly with inlining. To see further benefits of OSR for MATLAB, we shall develop more sophisticated optimizations that leverage the on-the-fly dynamic type and shape information that is very beneficial for generating better code.

5.4 Summary

In this chapter, we described how we have used the OSR machinery to implement dynamic incremental function inlining. We also described a symbol environment simplification optimization. On our benchmarks, we found some performance improvements and slight degradations, with several benchmarks showing good performance improvements.

We used our OSR strategy in the McJIT implementation, and using this implementation, we demonstrated the feasibility of the approach by measuring the overheads of the OSR instrumentation for two OSR placement strategies: outer-most loops and closest-enclosing loops. On our benchmark set, we found overheads of 0 to 4%.

Our ultimate goal is to use OSR to handle recompilation of key loops, taking advantage of type knowledge to apply more sophisticated loop optimizations, including parallelizing optimizations which can leverage GPU and multicores. Thus, as McJIT and MATLAB-specific optimizations develop, we plan to use OSR to enable such optimizations. In addition to our own future uses of our OSR implementation, we also hope that other groups will also use our OSR approach in LLVM-based JITs for other languages, and we look forward to seeing their results.

Chapter 6
Dynamic Function Evaluation with `feval`

As we mentioned in Section 1.3.3, MATLAB supports higher-order functions through the `feval` construct, which is widely used in many classes of numerical computations. A typical use of `feval` involves a dynamic evaluation of a function passed in as an argument to the function whose body contains the `feval` call [Mat09a]. For many classes of applications, such a dynamic evaluation of a fixed function is repeated in a long-running loop, and is often performed via interpretation.

This chapter focuses on determining if `feval` causes significant overheads in both the interpreter and JIT settings, and then proposes two mechanisms to optimize `feval`.

To determine potential overheads of `feval`, we identified a set of seven benchmarks that use algorithms that naturally use `feval`, and performed initial experiments on three interpreters (Octave, Mathworks MATLAB 7 in interpreter mode, and McVM in interpreter mode), plus two JITs (Mathworks MATLAB with the JIT enabled, and McVM with the JIT enabled). [1] These experiments showed, in both the interpreter and JIT situations, that there are significant overheads for calls via `feval`, as compared to direct function calls and inlined function calls.

To reduce the overheads of `feval` we then designed and implemented two alternative mechanisms. The first is the more general of the two mechanisms in that it can handle a wider variety of uses of `feval`, and is based on on-the-fly code generation and on-stack replacement (OSR) techniques implemented in McVM [LH13]. The OSR-based technique

1. Octave is an open source interpreter-only implementation which does not have a JIT.

identifies potentially important `feval` calls, and then uses McVM's OSR technology to specialize the `feval` calls to specific direct calls, and to provide correct backup to the general case when the specialized calls do not match the calling context. We describe the OSR-based approach in Chapter 7. The second mechanism extends the McVM JIT compiler with on-the-fly code specialization mechanism to specialize on the **value** of function parameters in those cases where the parameter is used inside the body of the function as the first argument to `feval`. This is described in Chapter 8.

This chapter describes our experiments that show significant overheads for calls via `feval` for important classes of benchmarks. The discussion here sets the stage for the descriptions, in Chapter 7 and Chapter 8, of our two mechanisms for reducing the overheads of `feval` calls.

6.1 Motivation and Problem

In this section, we provide some key background on MATLAB and its `feval` function, as well our experimental results that demonstrate the significant overheads of `feval`.

MATLAB and `feval`

In order to provide some intuition about MATLAB and the `feval` challenges, consider the example MATLAB function *newton* in Listing 6.1. As shown on line 1, the function takes four input arguments, with the first argument *fun* corresponding to either the name of a function or a function handle. Note that MATLAB has no declared types, although the programmer certainly has some expected types in mind, as indicated by the comments on lines 3 to 13. Indeed, not only does the programmer expect the first argument to be a string containing the name of a function, but she also expects the named function to take one input argument and produce two outputs. This is also clear from line 22, where `feval` is used to call the function provided by the argument *fun*. Listing 6.2 shows the definition of *fx3n*, which is one possible function that could be provided to *newton*.

Listing 6.1 – Newton's method to find a root of the scalar equation f(x) = 0, adapted from [Rec00a, Rec00b]. Function *fx3n* is shown in Listing 6.2.

```
function r = newton(fun,x0,xtol,ftol)

% newton      Newton's method to find a root of the scalar
%             equation f(x) = 0
% Synopsis:   r = newton(fun,x0,xtol,ftol)
% Input:      fun     = (string) name of mfile that
%                       returns f(x) and f'(x).
%             x0      = initial guess
%             xtol    = absolute tolerance on x.
%                       Smallest: xtol=5*eps
%             ftol    = absolute tolerance on f(x).
%                       Smallest: ftol=5*eps
% Output:     r       = the root of the function

  xeps = max(xtol,5*eps);
  feps = max(ftol,5*eps);   % Smallest tols are 5*eps
  x = x0;  k = 0;
  maxit = 15;  % Initial guess, current and max iterations
  while k <= maxit
    k = k + 1;
    % Returns f(x(k-1)) and f'(x(k-1))
    [f,dfdx] = feval(fun,x);
    dx = f/dfdx;
    x = x - dx;
    if (abs(f) < feps), r = x; return; end
    if (abs(dx) < xeps), r = x; return; end
  end
end
```

Listing 6.2 – Function *fx3n* from [Rec00a, Rec00b].

```
function [f, dfdx] = fx3n(x)
  % fx3n Evaluate f(x) = x - x^(1/3) - 2 and
  % dfdx for Newton algorithm
  f = x - x.^(1/3) - 2;
  dfdx = 1 -(1/3)*x.^(-2/3);
end
```

The MATLAB function `feval` is a built-in function, that is used in MATLAB to indirectly evaluate a function at run time. `feval` is overloaded, with two versions available:

```
[y1, y2, ...] = feval(fhandle, x1, ..., xn)
[y1, y2, ...] = feval(fname, x1, ..., xn)
```

where *fhandle* is a first class type in MATLAB which can be bound to a MATLAB built-in function or a user-defined function using the '@' operator. If the second version is used, then *fname* must be a string containing a single function name and cannot contain a path to a function or a directory. [2]

For our example program in Listing 6.1, a typical call would be one of the following:

```
newton(@fx3n, 3, 5e-16, 5e-16)
newton('fx3n', 3, 5e-16, 5e-16)
```

where the first case passes a function handle and the second case passes a string containing the name of the function.

Clearly algorithms such as *newton* are naturally parameterized over the evaluation function, and MATLAB's `feval` provides a mechanism for this abstraction. However, one might wonder if the use of `feval` causes any significant slow down. To determine this, we studied the cost of `feval` implementations in three implementations of MATLAB: (1) Mathworks' implementation for the MATLAB programming language; (2) Octave, a GNU [3] open-source implementation of the MATLAB language; and (3) McVM, our open source MATLAB framework.

The Mathworks' MATLAB system (called MATLAB in the tables) provides an interpreter for the language and also an accelerator (a JIT compiler). Octave is an interpreter for the MATLAB language. It does not have a JIT compiler. Like Mathworks' MATLAB, McVM has an interpreter and an optimizing JIT compiler.

We conducted our experiments on these systems over a set of MATLAB programs from numerical computing domains. These benchmarks include programs for finding the roots of polynomials and to integrate first order ordinary differential equations. All but one (*sim_anl* [4]) of our benchmarks were collected from [Rec00b]. We give a short description, together with a static count of the total number of `feval` calls in the program in Table 6.1. The table also shows the number of `feval` calls in a loop in each benchmark.

2. See `http://www.mathworks.com/help/matlab/ref/feval.html`.
3. www.http://www.gnu.org/software/octave/
4. http://www.mathworks.com/matlabcentral/fileexchange

BM	**Description**	**# `feval` (total)**	**# feval (in loops)**
bisect	Uses bisection to find a root of the scalar equation f(x) = 0	3	1
newton	Newton's method to find a root of the scalar equation f(x) = 0	1	1
odeEuler	Euler's method for integration of a single, first order ODE	1	1
odeMidpt	Midpoint method for integration of a single, first order ODE	2	2
odeRK4	Fourth order Runge-Kutta method for a single, first order ODE	4	4
gaussQuad	Composite Gauss-Legendre quadrature	1	1
sim_anl	Minimizes a function with the method of simulated annealing	2	1

Table 6.1 – `feval` benchmarks.

We conducted all our experimental work on a computer with the following configuration.

Processor: Intel® Core™ i7-3930K CPU @3.20GHz
RAM: 16 GB;
Cache Memory: L1 32KB, L2 256KB, L3 12MB;
Operating System: Ubuntu 12.04 x86-64;
LLVM Compiler framework: version 3.0;
McJIT: version 1.1; McOSR: version 1.1;
GNU Octave: 3.0.5;
MATLAB: Version 7.12.0.635 (R2011a) 32-bit (glnx86).

In Table 6.2 and Table 6.3, for each benchmark, we show the execution times for the three systems: Octave, MATLAB and McVM. For all our experiments, the execution times do not include the start-up cost of the VM/interpreter. under the JITs, the execution time of a benchmark is the average of 10 separate runs of the benchmark. In addition, only the execution time of the first run includes the compilation time. By taking the average of the execution times of 10 runs, we spread the compilation cost over the 10 runs. For the interpreters, the execution time is the average of 5 separate runs.

Table 6.2 gives the execution times measured in seconds when the benchmarks were interpreted under the three systems. Similarly, Table 6.3 gives the execution times, also measured in seconds, when the benchmarks were run with MATLAB and McVM JITs enabled. As we mentioned earlier, Octave does not have a JIT compiler.

In each table, the column labelled (F) gives the time for the original benchmark, with the `feval` call. The column labelled (D) gives the time when we the `feval` is replaced (by hand) with a direct call to the input function used to run the benchmark, and the (I) column gives the time when the function is inlined (by hand). The rightmost columns give the speedups of the (D) and (F) versions as compared to the original `feval` version.

These results are very interesting because they show that even for the interpreted cases there are substantial overheads for `feval`. When the `feval` is replaced by a direct call the speedups range from 1.05 – 1.23 for Octave, 1.00 – 1.15 for MATLAB, and 1.00 – 1.30 for McVM. When the direct call is inlined the speedups increase even more, ranging from

	Interpreter				
	`feval` (F) t(s)	direct (D) t(s)	inlined (I) t(s)	Speedup F/D	F/I
bisect					
Octave	19.94	17.36	12.85	1.15	1.55
MATLAB	5.43	4.85	2.40	1.12	2.26
McVM	3.60	3.60	2.40	1.00	1.50
newton					
Octave	19.04	16.60	11.02	1.15	1.73
MATLAB	6.23	5.64	3.13	1.10	1.99
McVM	6.20	4.80	3.73	1.30	1.66
odeEuler					
Octave	32.86	28.56	18.41	1.15	1.78
MATLAB	12.63	11.56	6.38	1.09	1.98
McVM	7.05	6.81	4.52	1.03	1.56
odeMidpt					
Octave	54.85	46.65	25.22	1.18	2.17
MATLAB	20.75	18.29	7.76	1.13	2.67
McVM	11.31	11.01	6.61	1.03	1.71
odeRK4					
Octave	101.80	82.74	40.45	1.23	2.52
MATLAB	36.09	31.25	10.68	1.15	3.38
McVM	21.10	19.95	11.33	1.06	1.86
gaussQuad					
Octave	20.12	17.97	14.22	1.12	1.42
MATLAB	13.29	12.90	9.89	1.03	1.34
McVM	3.77	3.71	2.90	1.02	1.30
sim_anl					
Octave	23.81	22.61	20.33	1.05	1.17
MATLAB	16.14	16.15	14.52	1.00	1.11
McVM	4.48	4.45	3.93	1.01	1.14

Table 6.2 – Interpreter: `feval` overheads as compared to direct and inlined calls.

	JIT				
	`feval` (F) t(s)	direct (D) t(s)	inlined (I) t(s)	Speedup F/D	F/I
bisect					
Octave	*	*	*	*	*
MATLAB	2.99	2.63	0.28	1.14	10.65
McVM	2.38	1.67	1.07	1.41	2.22
newton					
Octave	*	*	*	*	*
MATLAB	3.52	3.20	0.71	1.10	4.98
McVM	2.60	1.40	0.73	1.85	3.56
odeEuler					
Octave	*	*	*	*	*
MATLAB	2.65	2.40	2.11	1.11	1.26
McVM	4.61	0.58	0.73	7.97	6.29
odeMidpt					
Octave	*	*	*	*	*
MATLAB	3.21	2.91	2.17	1.10	1.48
McVM	7.10	0.67	0.65	10.56	10.91
odeRK4					
Octave	*	*	*	*	*
MATLAB	4.07	3.31	2.22	1.23	1.84
McVM	12.79	0.68	0.66	18.88	19.22
gaussQuad					
Octave	*	*	*	*	*
MATLAB	3.92	3.69	2.42	1.06	1.62
McVM	1.27	0.97	0.96	1.31	1.32
sim_anl					
Octave	*	*	*	*	*
MATLAB	3.38	3.31	2.22	1.00	1.11
McVM	3.47	2.51	2.21	1.38	1.57

Table 6.3 – JIT: `feval` overheads as compared to direct and inlined calls.

1.11 – 3.38.

The `feval` overhead for the JIT-based system are proportionally even higher. For the MATLAB JIT replacing the `feval` with a direct call results in speedups of 1.00 – 1.23, and for the McVM JIT the results are 1.31 – 18.88. Inlining the direct call results in large speedups for the MATLAB JIT of 1.11 – 10.65 and for the McVM JIT the results are 1.32 – 19.22.

One might be surprised that the overheads for both `feval` calls and ordinary calls appear to be so high for MATLAB. There are two reasons for this. First, the lookup semantics for function calls in MATLAB are quite complex, and without optimization they require a heavy-weight dynamic lookup based on the current directory, the current path, and the type of the dominant argument. Secondly, the presence of `feval` can disrupt the intra- and inter-procedural analyses needed to correctly approximate dynamic types and array shapes, which is a key factor in generating efficient code.

Focusing on the JIT results, it appears that the McVM JIT can achieve more benefit than the MATLAB JIT by just replacing an `feval` call with a direct call, even without inlining. This is because McVM does on-the-fly interprocedural shape analysis and function specialization, which is enabled as soon as the `feval` is converted to a direct call. Although we do not have access to the implementation of Mathworks' MATLAB JIT, these results would seem to indicate that the MATLAB JIT is not doing a similar interprocedural analysis and that it requires inlining to get a similar benefit.

6.2 Summary

MATLAB programmers often use `feval` to implement a wide variety of numeric solvers. `feval` provides a mechanism to pass function names or function handles as parameters. This use of `feval` is a very reasonable way to implement general-purpose solvers, but in this chapter we showed that `feval` incurs a significant performance overhead, both on interpreted systems and in existing JIT compilers.

Since we see potential speedups for all systems, for both interpreters and JITs, there does seem to be an important optimization opportunity for dynamically specializing

`feval` calls to direct calls, and then potentially inlining those direct calls. In the next two chapters, we present two techniques for runtime optimization of `feval` calls. In chapter Chapter 7, we present the first technique, which uses OSR technology for on-the-fly transformations of `feval` calls. The second technique, presented in Chapter 8, uses input arguments and values to specialize functions with `feval` calls.

Chapter 7
OSR-Based `feval` Specialization

This chapter presents the first of our two approaches to improving the implementation of `feval` calls in McJIT. The approach leverages the OSR implementation described in Chapter 4 to perform on-the-fly transformation of `feval` calls in the body of a long-running loop. We begin the chapter with a description of the implementation of the approach. At the end of the chapter, we discuss our experimental results, which show that our OSR-based approach to `feval` calls specialization can be used to obtain good performance improvements.

The main contributions of this chapter are:

OSR-based specialization of `feval`: We developed a general technique to detect and instrument important `feval` sites with OSR points, and we designed an OSR-based transformation which can be done at the LLVM IR-level, without requiring access to the generated assembly code. We also designed appropriate JIT-time tests to optimize the guards required to determine if the specialized call could be made or if the general backup path should be taken.

Implementation in McVM/McOSR: We implemented the proposed approach in McVM. Our implementation is open source.

Experimental Results: We evaluated the approach on the set of benchmarks described in Section 6.1.

7.1 `feval` in McVM

As in most implementations of the MATLAB language, the code generated for an `feval` call by our JIT compiler can be significantly less efficient.

An `feval` call often prevents compiler optimizations because its input function cannot, in general, be determined until the run time. In MATLAB, the value of the input function of an `feval` call — which we shall from now call *`feval` evaluated function* (*fef*) — can be formed dynamically (e.g., a string formed by a concatenation of some run-time values). The value can also come from a data structure (e.g., an array or a struct) or as a return value from a function call.

When McJIT encounters a MATLAB statement involving a call to `feval`, it generates LLVM code to call to a dynamic dispatcher. For example, when for the `feval` statement at line 22 of Listing 6.1, it generates the code in Listing 7.1. Let us examine this code snippet. The compiler generates the code to save the arguments to the `feval` call into an array of objects. This is shown in lines 1–5. Then, it generates the call to the dynamic function dispatcher, that is, the call to Interpreter :: callFunction in line 6.

Listing 7.1 – LLVM code generated for an `feval` call.

```
1  %argsPtr = call i8* @"ArrayObj::create"(i64 2)
2  call void @"ArrayObj::addObject"(i8* %argsPtr,
3                                   i8* %arg1)
4  call void @"ArrayObj::addObject"(i8* %argsPtr,
5                                   i8* %arg2)
6  %retVal = call i8* @"Interpreter :: callFunction"
7                                  (i8* %funcPtr,
8                                   i8* %argsPtr,
9                                   i64 %nargout)
```

When the dispatcher is called at run time, it examines its first argument to determine that this is an `feval` call site. It then calls the library function `feval` passing it its own second argument — the array containing the arguments to the `feval` call. The `feval` library examines its own first argument and determines the right function to dispatch. It then prepares the input arguments needed by this function and calls the function. The result of executing this function is what the dispatcher eventually returns in line 6.

The foregoing procedure can be slow, and furthermore, it inhibits function inlining and other flow analyses. However, since the value of the function that `feval` built-in evaluates at run time cannot be determined statically in general, this implementation represents what is typically done to implement the `feval` library function.

A key point to note is that function binding and the argument types of the function called by `feval` often do not change through the whole loop execution, or even through the whole method execution, as is the case for the typical example in Listing 6.1. For this class of MATLAB programs, we can improve the runtime performance if it is possible to dynamically do on-the-fly code transformation and function specialization and possibly inlining.

7.1.1 OSR Background

McVM has support of OSR (Chapter 4) which works completely at the LLVM IR level. The main idea is that LLVM IR instructions can be tagged as interesting, and OSR points can be inserted on any loop that encloses the tagged instructions. Each OSR point is associated with an LLVM-IR transformer, which is applied when the OSR point triggers. The OSR library takes care of saving the appropriate state, and restarting the transformed code at the appropriate location and state. In the next section, we provide the details of how we leverage the OSR machinery to optimize `feval`.

7.2 OSR-Based `feval` Transformation

In Section 6.1, we discussed the cost of `feval` in MATLAB programs and the challenges to an efficient implementation of `feval` in a MATLAB JIT compiler. We begin this section with a short discussion of the objectives for our approach to optimize `feval`, and then we highlight the major steps in our approach to on-the-fly specialization using OSR.

7.2.1 `feval` Optimization Goals and Strategy

In Listing 7.1 we illustrated the code currently generated for a call to `feval`. Line 6 contains the key problem, which is an indirect call to the interpreter callFunction method that is required in order to dispatch to the correct function.

The aim of our approach is to replace the call to the dispatcher with a direct call to the function given as the first argument to the `feval` call while maintaining the correctness of the code. To maintain correctness, we will need some safety checks that will backup to the general case if the current call does not match the last specialized version. Thus, another key challenge is minimizing the overhead for the check.

Our solution strategy has three important steps, the first two steps are done at JIT-compilation time (for example, when function *newton* is first JIT-compiled), whereas the third step happens at run time (for example, when the while loop inside of *newton* executes).

Dispatcher call annotation: During JIT-compilation of a function body, all dispatcher calls that correspond to `feval` calls in a loop must be identified and marked. This is discussed in detail in Section 7.2.2.

OSR instrumentation: If the first phase identifies some `feval` dispatcher calls, then the closest enclosing loop of each such dispatcher call must be instrumented to include a conditional OSR trigger, usually based on the number of loop iterations. In addition, an OSR point must be inserted, where the OSR point is associated with the `feval` optimizing transformation. We discuss this further in Section 7.2.3.

Triggering an OSR event at run time: At run time, if an OSR is triggered by a running function, the code transformer attached to that OSR point will be executed. In our approach, this is where the `feval` optimizing transformation is actually performed. This transformation must rewrite the LLVM IR to replace the annotated `feval` call with the appropriate direct (or inlined) call, and it must also insert appropriate guards to ensure that the specialized call is only executed for the correct specialized function and argument types, and it must backup to the general case otherwise. We give a detailed description of the code transformer in Section 7.2.4.

7.2.2 Dispatcher Call Site Annotation

As mentioned in the introduction to this section, we have added a pass to the McJIT compiler to identify all the calls to the dispatcher that correspond to an `feval` call. These call sites are annotated with the OSR ID of their closest enclosing loop. For example, for the `feval` call in Listing 7.2, the following would be generated:

%retV = call i8∗ @"Interpreter :: callFunction "(i8∗ **%funcPtr**,
i8∗ **%argsPtr**, i64 **%nargout**), !FI !OSR1

where !FI and !OSR1 are the metadata used to annotate the call sites with the call to the dispatcher for an `feval` call. The string !OSR1 indicates that this call site will be considered for an `feval` optimizing transformation if OSR is triggered in the loop identified with OSR ID 1.

We also assign a unique ID to each `feval` call site. This ID is used to index a fixed memory area for caching the types that the arguments to the dispatcher had just before OSR is triggered at run time. To facilitate this process, a store instruction of the following form is generated:

store i8∗ **%argsPtr**, i8∗∗ addrOfCacheSlot, !FI

which stores the pointer to the array of objects passed to the dispatcher to a fixed cache slot associated with the current `feval` call. Notice that this instruction is also annotated with the same metadata as the call to the dispatcher.

The metadata !FI encapsulates some JIT-time information about the arguments of the associated `feval` call. It is a 3-tuple. The first operand or field is the unique ID assigned to this `feval` call; the second and the third represent relevant JIT-time facts about the `feval` call site. We defer the discussion on the information collected at the JIT-time to Section 7.2.5.

The annotations attached to the call to the dispatcher are consumed by the code transformer during an OSR event. We discuss the transformer in more detail in Section 7.2.4.

7.2.3 OSR Instrumentation

At JIT compilation time for a function, if a loop contains an `feval` call, the loop must be instrumented with a test that determines whether a loop counter has reached a given threshold. This is the OSR condition. We experimented with a threshold value set at 2. So, at run time, after the execution of the second iteration of the loop, the OSR condition will be satisfied. The conditional execution of the OSR point is achieved by generating the following LLVM conditional instruction at end of the loop header.

br i1 **%osrCond**, label **%OSR**, label **%LB**

This instruction inspects the OSR condition (**%osrCond**) and branches to the basic block named **%OSR** (which triggers the OSR) if the test is successful. Otherwise, it branches to **%LB** where the body of the loop will be executed as normal.

For our `feval` optimization, we use a closest-enclosing-loop strategy for the placement of an OSR point. The McOSR library requires that each OSR point is associated with a code transformer - it is this transformer that will execute when the OSR triggers. Thus, our `feval` optimizing transformation logic is implemented by the code transformer that we attach to the inserted OSR point. Our code transformer has the following signature:

void transformFeval (llvm :: Function∗ F, osr :: OSRLabel L);

where F is the LLVM IR of the function that has triggered an OSR event, and L is the OSR label of the loop where an OSR has been triggered. We discuss in detail the logic of the code transformer in Section 7.2.4.

Listing 7.2 shows a code snippet from our running example, and in Figure 7.1, we show in a simplified form, the corresponding control flow graph (CFG) in LLVM IR. *LH1* is the loop header block and terminates with a conditional branch instruction. The basic block branches to the loop body at *LB* or the loop exit block at *LE* depending on the loop exit condition (*%loopExitCond*).

Listing 7.2 – ***while*** loop extracted from (Listing 6.1).

```
1     ...
2     while k ≤ maxit
3         k = k + 1;
4         [f, dfdx] = feval(fun,x);
5          ...
6     end
7  end
```

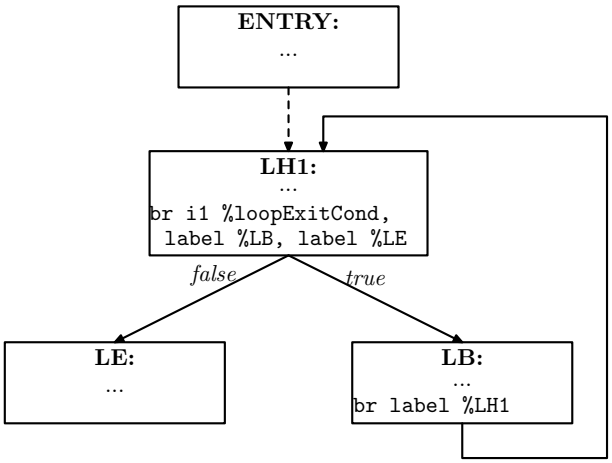


Figure 7.1 – A CFG for the MATLAB ***while*** loop in Figure 7.2.

The CFG shown in Figure 7.1 is transformed into that shown in Figure 7.2 after inserting an OSR point. As can be observed from the figure, the loop header block now contains the instruction to compute the OSR triggering condition (**%osrCond**) and terminates with a conditional branch instruction as discussed earlier.

7.2.4 OSR Triggering and Runtime Transformation

At the heart of our implementation is the code transformer that is attached to an OSR point. When an OSR is triggered at run time, the OSR runtime system passes control to the code transformer. This is where our `feval` optimizing transformation is performed.

The code transformer first traverses its input function (i.e, the LLVM IR of the running function) and collects all the calls to the dispatcher that are associated with an *feval* call

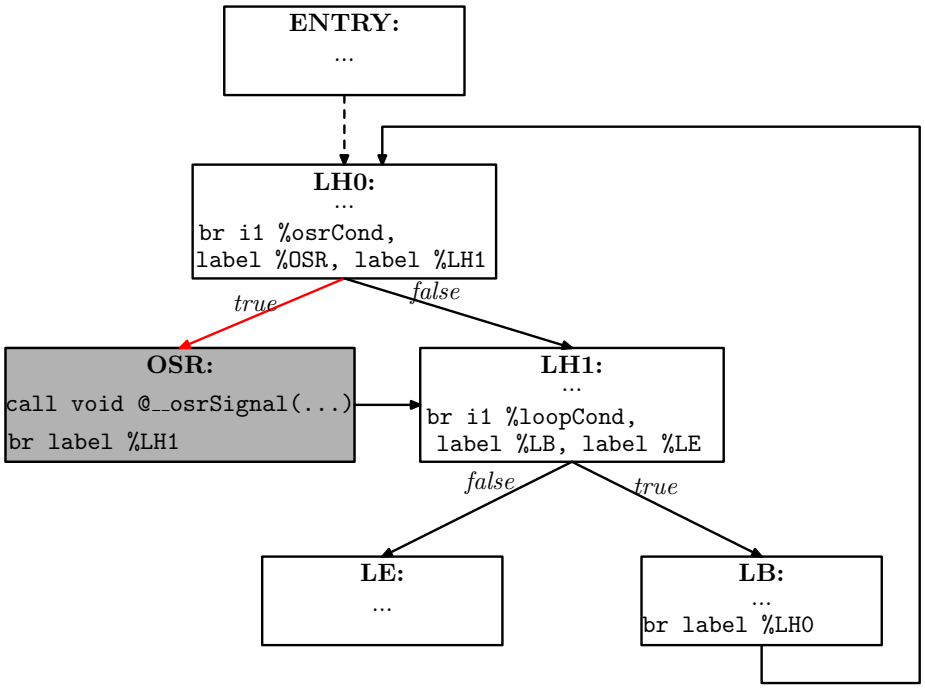


Figure 7.2 – The CFG of a loop with an OSR point.

site in the source program. The transformer can identify these call sites using the OSR label attached to such instructions at their creation time. The transformer also identifies and removes all the `store` instructions that were inserted to cache the last-known types for the arguments to the dispatcher.

The transformer then processes the call instructions as follows. For each dispatcher call, the transformer extracts the cache slot ID of the current call dispatcher. It then uses the cache slot ID as an index into the cache to retrieve the pointer to the array of objects containing the last arguments passed to the dispatcher. Using this pointer, the code transformer determines the function being dispatched — the *fef* — at this call site. However, if the cache slot is unset, the processing of the current call is aborted and the code transformer continues with the next call.

Having determined precisely the function passed to `feval` at this call site, the transformer begins a series of transformations at the basic block containing the current call. We illustrate the actions of the code transformer in Figure 7.3 and Figure 7.4.

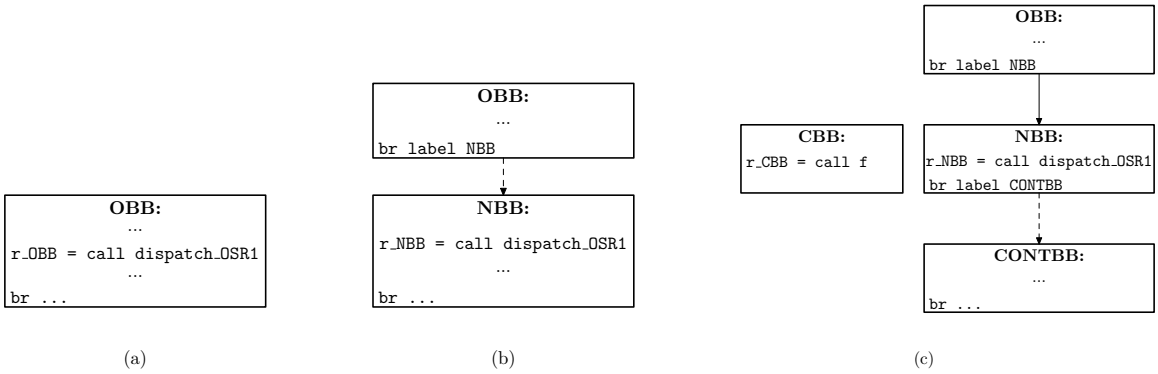


Figure 7.3 – Actions of the code transformer. Basic block *OBB* in (a) is split into two. The result of the splitting process is shown in (b). In (c), *NBB* is split into *NBB* and *CONTBB*. A new unlinked basic block named *CBB* is also generated. *CBB* contains a call to the new compiled function (f).

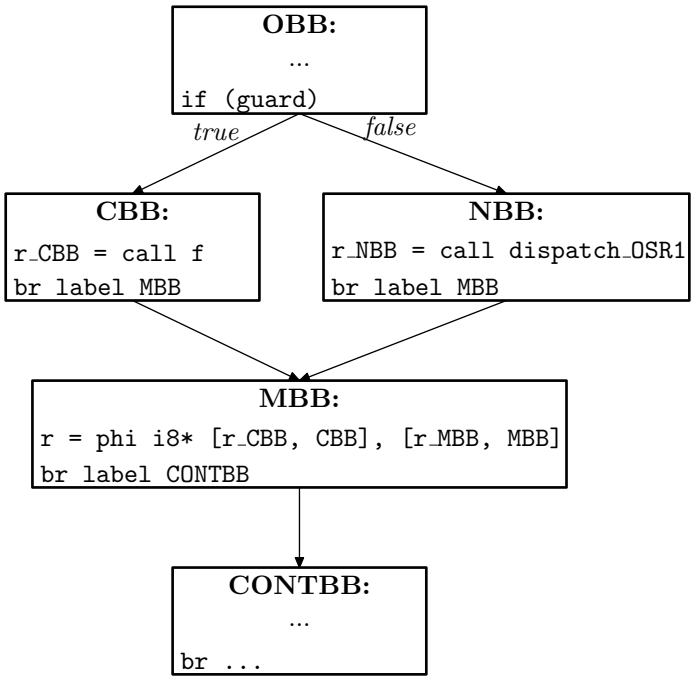


Figure 7.4 – Actions of the code Transformer. Two new basic blocks have been inserted into the CFG: *CBB* contains a call to the compiled function (f), and *MBB* merges the results from the call in *CBB* and the original call to the dispatcher in *NBB*.

Figure 7.3(a) shows a basic block (*OBB*) with a call to the dispatcher, represented with *dispatcher_OSR1*. As shown in the figure, the call to the dispatcher is annotated with OSR label *OSR1*.

The transformer first splits the original basic block (*OBB* in Figure 7.3(a)) to obtain the basic blocks shown in Figure 7.3(b). In Figure 7.3(b), the call to the dispatcher in *OBB* has been moved into the beginning of a new basic block named *NBB*.

Later, the transformer forms a string from the types determined for the last arguments passed to the dispatcher. This string forms a key into the code cache. Recall that McJIT caches code based on the types of the arguments passed to a function at a call site. The code transformer inspects the code cache using this key. If no matching compiled code is found, the code transformer calls the compiler to compile the function. Let us call such a newly compiled function f. Note that the code transformer may choose to inline f if it considers it as a good inlining candidate and performs further optimizations on the calling function as well.

After the compilation, the transformer creates a new basic block and creates the instructions to call the compiled function (f). This new block is shown in Figure 7.3(c) as *CBB*. To terminate *CBB*, the code transformer must first determine the continuation block. Of course, after the call to f in *CBB* returns, the execution must continue with the code after the call to the dispatcher in the original block (*OBB* in Figure 7.3(a)). Thus, the code transformer splits *NBB* after the call to the dispatcher to obtain a new basic block *CONTBB*. This is the continuation block for *CBB*.

Now, we have two alternative paths to evaluating function f: (1) via a direct call in *CBB* and (2) via the call to the dispatcher in *NBB*. Because the code in the current *OBB* (Figure 7.3(c)) is always executed before the call to the dispatcher in the original *OBB* (Figure 7.3(a)), it must follow that the current *OBB* dominates both *CBB* and *NBB*. Thus, the code transformer terminates *OBB* with a runtime *guard*. We discuss the *guard* in the next section. The transformer also creates a new basic block named *MBB*. As shown in Figure 7.4, *MBB* merges the results from *CBB* and *NBB* via a *phi* instruction generated by the code transformer. *MBB* then terminates with a branch to the continuation block, *CONTBB* as shown in Figure 7.4.

The code transformer essentially implements our OSR-based `feval` optimization. To

some degree, the runtime performance depends on the cost of evaluating the *guard* that determines the execution path taken at run time. We now discuss the functions of the *guard*.

7.2.5 Runtime Guards

The code transformer generates a runtime guard (shown in Figure 7.3(c)) that will determine the path taken by the program at run time. It chooses from among several guards depending on the quality of the metadata it retrieved from the call instruction that calls the dispatcher. In Section 7.2.2, we mentioned that we collect a variety of JIT compilation-time facts on `feval` call sites in the *!FI* metadata. The second component of the metadata is an unsigned integer that encodes three bits of information, corresponding to the following queries.

1. Is the first argument to an `feval` call a read-only variable in the function? We shall denote this query with *ROQ*.
2. Is the first argument a loop constant variable? We shall use *LCQ* to denote this query.
3. Do all the arguments to the `feval` call have a fixed runtime type? We shall denote this with *FTQ*.

The first two pieces of information are computed at JIT compilation time using standard flow analyses. The third is computed using McJIT's type inference [CBHV10], which starts with the actual runtime types for all arguments to the function and infers a set possible types for each variable at every program point. Therefore at the call to an `feval`, the type-inference can determine the set of possible types for all the arguments to the `feval` call. If only one type exists in the type set for each argument, then *FTQ* is true.

The combination of these queries guides the choice of the guards generated by the transformer. If *ROQ* is true, we can move the part of the computation of the guard (to determine whether or not the runtime value of this argument corresponds to the function that will be called at *CBB* shown in Figure 7.4) to the function's entry block.

If *LCQ* is true, we can compute the guard outside the loop and use the result to determine the path taken by the program after *OBB*. If *FTQ* is true, it means that all the

arguments are monomorphic and we can completely eliminate the check that determines whether the type of any argument changes at run time. We discuss this further below.

Let

f**:** denote the first argument to an `feval` call;

P**:** denote the set of the remaining arguments p_2, p_3, ..., p_n to the `feval` call;

***lastValue*(f):** denote the cached value of f;

***newValue*(f):** denote the current value of f;

***lastType*(p):** denote the cached type of variable p;

***newType*(p):** denote the current type of variable p.

FEB: be the entry basic block of a function containing an `feval` call; and

LEB: be the entry basic block of a loop with an `feval` call.

We enumerate in Table 7.1, the different possible guards (based on the three queries) that the code transformer can generate together with the optimal point to compute a guard.

To simplify the table, we define

$$\begin{aligned} f\_cond &= \textbf{\textit{lastValue}}(f) == \textbf{\textit{newValue}}(f) \\ a\_cond &= \forall(p \in P), \textbf{\textit{lastType}}(p) == \textbf{\textit{newType}}(p) \end{aligned}$$

and write *f_cond* (*FEB*) if *f_cond* should be computed at the entry basic block of the function containing a corresponding `feval` call.

Let us examine Table 7.1. In the first case (i.e., table row 1), *ROQ*, *LCQ*, and *FTQ* are true, in this case, only *f_cond* should be computed and can be done at *FEB*, that is, the calling function's entry basic block. *FTQ* is true. Thus, we know that the runtime type of each argument at the `feval` call site is fixed so, there is no need to include *a_cond* in the *guard* that is evaluated at *OBB*.

In Case 2 (i.e., table row 2), the required guard that the code transformer must generate is: $guard = f\_cond \wedge a\_cond$. This is because the type of each argument to f may change at run time. Furthermore, if after transforming the code, the value of f changes (i.e., in a subsequent call of the function with the `feval` call), the backup path must be taken. The *f_cond* component of the guard can be evaluated at the function's entry basic

#	*ROQ*	*LCQ*	*FTQ*	Guard	Compute Point
1	T	T	T	*f_cond*	*f_cond* (*FEB*)
2	T	T	F	*f_cond* ∧ *a_cond*	*f_cond* (*FEB*); *a_cond* (*OBB*)
3	T	F	T	*	*
4	T	F	F	*	*
5	F	T	T	*f_cond*	*f_cond* (*LEB*)
6	F	T	F	*f_cond* ∧ *a_cond*	*f_cond* (*LEB*); *a_cond* (*OBB*)
7	F	F	T	*f_cond*	*f_cond* (*OBB*);
8	F	F	F	*f_cond* ∧ *a_cond*	*f_cond* (*OBB*); *a_cond* (*OBB*)

Table 7.1 – Guard truth table (a "*" denotes an impossible result).

block because f is read-only in the calling function. It must be a parameter of the function. However, because the types of the arguments may change before the `feval` call site, the second component of the guard, *a_cond*, must be evaluated just before the use of the guard in basic block *OBB*.

Cases 3 and 4 represent impossible cases because it cannot be that f is a read-only variable in the calling function and at the same time not be a loop constant in that function.

In Case 5, only *f_cond* should be computed and this can be done at *LEB*.

Case 6 is similar to Case 2 except that *ROQ* is false, meaning that f is not a read-only variable but it is a loop constant. For this reason, like Case 2, the required guard is $guard = f\_cond \wedge a\_cond$. Unlike Case 2, however, the optimal point to compute *f_cond* is at *LEB*. The second component (*a_cond*) must still be computed at *OBB*.

In Case 7, we know that the arguments have constant types at the `feval` call site. But we also know that f is neither a read-only nor a loop constant. So, the required guard is to evaluate only *f_cond* at *OBB* before the use of the guard.

Case 8 requires that both *f_cond* and *a_cond* be computed at *OBB* before the use of the guard in the block. This is because f is neither a read-only nor a loop constant variable.

Further, the types of the arguments may change at run time as indicated by the value of *FTQ* in row 8 of Table 7.1. Observe that this is the most expensive guard computation the code transformer can generate.

The least expensive guard is in Case 1. This is the ideal case. In the worst case (Case 8), the code transformer inserts a relatively expensive guard at the end of *OBB* that tests whether the current runtime value of *fef* (of an `feval` call) corresponds to the compiled function and that the remaining arguments have stable types. This may have an impact on performance, although we believe this seldom happens within the class of the applications that we have considered.

7.2.6 Resuming Execution after an OSR is Triggered

You will note that we have only focused on defining the OSR points and the transformation that occurs when an OSR triggers, but have not defined how the newly transformed code is executed and how the state is restored or how control flow is correctly resumed. These important details are handled automatically by the McOSR library [LH13].

7.3 Experimental Results

In Section 6.1, we demonstrated that `feval` resulted in significant overheads, and that replacing an `feval` by a direct call resulted in substantial speedups, which could be further increased by inlining the direct call. In this section we examine the performance improvements achieved through our OSR-based specialization presented in Section 7.2. We examine both the benefits and limitations of the approach, and we compare its performance with the upper bound speedups provided under the hand-coded direct call and inlined versions.

In Table 7.2, the column labelled **Baseline** shows the results of executing the benchmarks with McVM JIT in the normal mode. The columns labelled **OSR-based Optimization** give the execution times for three variations of the OSR approach. *Opt0* gives the results when the benchmarks were run with our basic OSR-based `feval` optimization enabled. We also experimented with two further improvements. The column labelled *Opt1* shows the benchmarks with the OSR-based `feval` optimization plus a dynamic function

	Baseline	**OSR-based Optimization**						**Hand-coded**	
	t(s)	t(s)			Speedup			Speedup	
Benchmark	Baseline(F)	Opt0	Opt1	Opt2	F/Opt0	F/Opt1	F/Opt2	F/D	F/I
bisect	2.38	1.93	1.92	1.93	1.23	1.24	1.23	1.41	2.22
newton	2.60	2.23	2.23	1.55	1.17	1.17	1.68	1.85	3.56
odeEuler	4.61	2.71	2.82	2.64	1.71	1.63	1.75	7.97	6.29
odeMidpt	7.10	4.22	4.18	4.15	1.68	1.70	1.71	10.56	10.91
odeRK4	12.79	7.35	7.46	7.36	1.74	1.72	1.74	18.88	19.22
gaussQuad	1.27	1.03	1.04	1.05	1.23	1.22	1.21	1.31	1.32
sim	3.47	3.40	3.36	2.98	1.02	1.03	1.16	1.38	1.57
Geometric Mean					1.37	1.36	1.47	3.58	4.16

Table 7.2 – Overall results for OSR-based optimitimzation in McVM JIT

inlining optimization that is performed when the OSR point triggers. *Opt2* is a further improvement where we first apply the dynamic inlining, and then apply a further optimization of the symbol table environment, which is sometimes enabled by the inlining. We describe this optimization in more detail in our discussion of the performance of this optimization.

From the results, we found that our `feval` optimization was effective. McJIT with the `feval` optimization consistently outperforms the standard McVM JIT on our benchmark set. The geometric mean of speedups at *Opt0* is 1.37. The dynamic inlining optimization enabled by *Opt1* does not improve performance on its own, but in combination with the subsequent symbol table optimization enabled for *Opt2*, there is an improvement, with a geometric mean speedup of 1.47.

At optimization level 2 (*Opt2*), we recorded the highest performance improvements with the *newton* and *sim* benchmarks. In McVM, the interaction between the compiled code and the interpreter is often facilitated through a symbol look-up environment. A symbol environment is a table that associates a value to a symbol. It is used to bind a value to a variable, and to look-up the value of a variable at run time. When needed, McJIT inserts the instructions to set up a symbol look-up environment for a function at the function's prologue. The set-up code initializes the environment for subsequent look-ups and bindings of values to variables. This can be a major source of overhead. After dynamic inlining, we

perform an optimization that eliminates redundant set-up code. We found that the interaction simplification was particularly effective in two of the benchmarks: *newton* and *sim*, which contained significant redundant setup code after inlining.

Although speedups of 1.47 are good, it is also important to examine if our dynamic optimization is approaching the upper bound speedups that we measured by hand-coding the direct call and hand-lining that call. The last two columns show the speedups we had measured for the hand-coded versions, and we see that the geometric mean speedups were 3.58 for the direct call and 4.16 for the inlined call. Thus, there is still a significant gap between what the dynamic technique achieves and the upper bound.

To see why this is the case, we examined the kinds of the runtime guards and the LLVM code generated for our benchmarks. We show the kinds for each benchmark in Table 7.3, with column *# feval (in loop)* showing the number of `feval` calls in the loops of a benchmark. We show the kinds of the runtime guards generated for the `feval` calls in a benchmark under column *Types of Guards*.

Benchmark	# `feval` **(in loop)**	**Types of Guards**
bisect	1	Case 1 [a]
newton	1	Case 2 [b]
odeEuler	1	Case 2
odeMidpt	2	Case 2
odeRK4	4	Case 2
gaussQuad	1	Case 1
sim_anl	1	Case 1

a. According to Table 7.1, Case 1 means that only the value of the *fef* is checked at the function's entry basic block. The types of the arguments to the `feval` call are stable.

b. According to Table 7.1, Case 2 means that the value of the *fef* is checked at the function's entry basic block; while the types of all the arguments are checked in the loop containing the `feval` call.

Table 7.3 – Types of the runtime guards used by each benchmark.

We can see from Table 7.3 that a somewhat expensive guard — one that checks the value of the *fef* passed in at the *entry* basic block and the types of *all* the arguments to an `feval` call in a loop — is generated for each `feval` call in the *ode* benchmarks. This is the case because the type inference engine infers that the type of at least one of the arguments is variable or *unknown*. This can be a source of runtime overhead. In addition, because the type-inference infers that the type of an argument to the target function of each `feval` call in the *ode* benchmarks is variable, the LLVM code generated for the *ode* benchmarks is less efficient. This is the main reason for the relatively lower performance recorded for the OSR-based version running the actual *ode* benchmarks. We continue this discussion in Section 8.2.2, where we compare the performance results discussed here with those obtained for the benchmarks under our second mechanism for `feval` call specialization.

We conclude that converting an indirect call to a direct call can reveal good optimization opportunities that may be exploited for a performance improvement. Our OSR-based `feval` optimizing transformation technique is effective and practical. We will continue to improve our optimizer and we believe that our technique can be used to improve performance in similar JIT compilers.

7.4 Summary

We proposed a general on-the-fly mechanism for specializing `feval` calls in hot loops using the OSR mechanism available in McVM, an open source research virtual machine for MATLAB. We demonstrated good performance improvements using the approach.

In the next chapter, we present a different approach that uses parameter values to specialize functions with `feval` calls. We then compare the performance of this new approach with our OSR-based approach.

Chapter 8
JIT Value-Based Specialization

We presented in Chapter 7, the first of our two approaches to specializing `feval` calls. In this chapter, we present the second approach, which extends the McJIT type-specialization mechanism. The approach named JIT value-based approach specializes functions with `feval` calls using the runtime values of the arguments to the function. It is based on the observation that, for some class of MATLAB programs, a function with an `feval` call often accepts as an argument the name or the function handle to a function evaluated by the `feval` call. Further, the call is often executed repeatedly within a long-running loop, which, as we showed in Chapter 6, can cause a major performance slow down.

The main contributions of this chapter are:

JIT value-based specialization: We designed an extension to the McVM JIT specialization mechanism. Previously specialization was performed based only on the dynamic **types** of function arguments. In the new approach, we also specialize on the **value** of a function argument, for the case where that argument is used as the first argument to a call to `feval` inside the body of the function to be compiled.

Implementation in McVM/McOSR: We implemented the proposed approaches in McVM. Our implementation is open source.

Experimental results: We evaluated the JIT value-based approach. We also compared the JIT value-based approach with the OSR-based approach presented in Chapter 7.

Our JIT-time code specialization for `feval` replaces calls to a function that has an `feval` call with a call to a special dispatch function. This dispatch function (called the dispatcher for short) evaluates the value of the parameter that corresponds to an *fef*. It then generates a new version of the function with all the `feval` calls replaced with direct calls to the *fef*. This is illustrated in Figure 8.1.

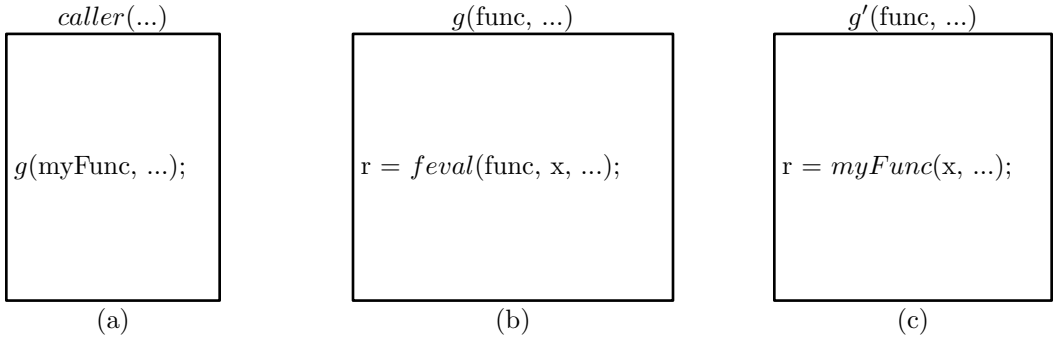


Figure 8.1 – `feval` Runtime Code Specialization.

In Figure 8.1, function *caller* calls function g. As shown in (b), function g has an `feval` call that evaluates one of its parameters, namely *func*. Function *caller* calls g with an argument, *myFunc*, which references a function (e.g., a function handle or a function name). This is the function that the `feval` call in g will evaluate.

However in Figure 8.1(c), a new version of function g named g' is created and all the `feval` calls that evaluate *func* have been replaced with direct calls to function *myFunc*.

In the next section, we describe in detail the implementation of this approach.

8.1 JIT Code Specialization

During the parsing of the XML string for a compilation unit (i.e., a list of MATLAB functions in a MATLAB mfile (Figure 2.3)), McJIT analyzes all the functions in the compilation unit and annotates those with an `feval` call, whose *fef*, that is, the first parameter, is a read-only parameter of the enclosing function.

Normally, after McJIT has compiled the right version of a function at a call site, it inserts the corresponding LLVM call instruction into the current basic block. However, to

support the runtime code specialization for `feval`, we modified McJIT so that it does not insert the call instruction but, instead, generates a new instruction of the form

```
call void @''JITExt::dispatchFunction''(i8* %baseIRPtr,
                                        i8* %fefValue,
                                        i8* %inArgsPtr,
                                        i8* %retValsPtr,
                                        i32 %csID)
```

that calls the dispatcher. The dispatcher, that is, function *JITExt::dispatchFunction*, accepts five arguments:

(1) the first is the pointer to the base IR (i.e., the original version of the IR) that corresponds to the called function at the call site;

(2) the second is a pointer to the argument that corresponds to the *fef* (i.e., the first parameter) of a marked `feval` call in the called function;

(3) the third is a pointer to a structure containing the input arguments to the called function;

(4) the fourth is a pointer to a structure containing the return values;

(5) the last argument is an integer that denotes the index of a cache slot where a pointer to the descriptor of the AST can be located.

Each AST representing a function with an `feval` call has one or more code cache descriptors. A code cache descriptor contains information related to the code of the AST that corresponds to the types of the arguments passed to the function at a call site.

A function that is called with different argument types at different call sites has a code cache descriptor for each call site. A code cache descriptor is a four-tuple.

$$descriptor = < entry\_address, argument\_types, counter, feval\_versions >$$

where *entry_address* is the address of the entry to the compiled code corresponding to the AST of the called function. We shall denote the called function at a call site with f. Field *argument_types* denotes the types of the arguments at the call site. Due to McJIT's code specialization on argument types at call sites, the set of types for the arguments at a call

site is immutable. Field *counter* denotes a compilation counter that counts the number of versions that are generated at different consecutive executions of the call to the dispatcher instruction. Field *feval_versions* is a map containing (*AST , entry_address*) pairs. The first member of the pair is the IR corresponding to the value of the parameter used as the first argument to some `feval` calls in f. The second member of the pair is the address of the entry point to the compiled code of f that corresponds to an *fef*.

8.1.1 Functions of the Dispatcher

At run time, the dispatcher first uses a combination of its first parameter (i.e., the AST) and its last parameter (i.e., the cache slot index) to retrieve the code cache descriptor that matches the argument types at the current call site. This is shown in line 1 of Algorithm 2. Then, in line 2, the dispatcher performs a look-up using its second parameter to determine whether a corresponding code version had been generated.

If the look-up is successful, the dispatcher executes (in line 13 of Algorithm 2) the function at the address returned by the look-up.

Otherwise, the dispatcher compares the current value of the counter in the code cache descriptor with a given *threshold*. If the counter has exceeded the threshold, the dispatcher executes the initial code generated for the AST at this call site. This is shown in line 15 of Algorithm 2. If the counter is below the threshold, however, the dispatcher clones the original AST and replaces all the marked `feval` calls with direct calls to the evaluated function given as its second parameter. After, the dispatcher retrieves the types attached to this call site and calls the compiler to compile and generate the correct code matching the argument types at this call site. These actions are performed in lines 3 – 11 of Algorithm 2.

After the compilation of a new version, the dispatcher inserts an entry — that is, a pair comprising of the AST corresponding to the current value of the *fef* and the entry point address of the compiled code — into a map in the code cache descriptor of the base IR. This action is performed by the call of function *putNewVersion* in line 9 of Algorithm 2. The dispatcher does this so that if the function is called again with the same *fef* value, it can retrieve and execute the correct code. Finally, the dispatcher updates the counter associated with the cache slot descriptor.

```
   input  : baseIR, fef, inArgPtr, outArgPtr, cacheSlot
   output: void
 1 ci ← getCodeCacheInfo (baseIR, cacheSlot);
 2 entryPoint ← lookupFunction (ci, fef);
 3 if entryPoint == NULL AND ci.counter <= THRESHOLD then
 4 |   newIR ← clone (baseIR);
 5 |   replaceFevalCalls (newIR, fef);
 6 |   llvmIR ← compileFunction (newIR, ci.argTypesStr);
 7 |   entryPoint ← compCallWrapper (llvmIR, newIR, ci.argTypesStr);
 8 |   // insert an entry for a new version into the cache;
 9 |   putNewVersion (ci, getFunction (fef), entryPoint);
10 |   ci.counter ← ci.counter + 1;
11 end
12 if entryPoint ≠ NULL then
13 |   call entryPoint (inArgsPtr, outArgsPtr);
14 else
15 |   call ci.entryPoint(inArgsPtr, outArgsPtr);
16 end
```

Algorithm 2: dispatch function

Although the base AST and new versions of the AST have the same number of input and output parameters, the types of the values returned by the compiled code that corresponds to a given *fef* may be different. This presents a problem in that the rest of the code of the calling function was generated using the information obtained from the base AST. We resolved this problem by generating a wrapper (line 7 of Algorithm 2) that converts from the types returned by a new version to the types used in generating the code for the original version. Because of this problem, we always call the code that matches an *fef* via a wrapper.[1] A wrapper is a short function. It is composed of a call instruction and the instructions that convert the return values to their expected types.

A code cache look-up miss causes a compilation of a new version if the value of the counter in the code cache descriptor has not exceeded the threshold. After the counter has exceeded the given threshold, the dispatcher stops compiling new versions. Thus, for a new *fef* value, the dispatcher then always executes the original code generated for the base AST of the called function. This scheme can prevent excessive compilation actions in cases where too many different functions are being called. However, this rarely happens in practice. So, we expect only a reasonable number of new versions to be generated.

Again, we stress that this approach only works in cases where the *fef* of an `feval` call in the called function is a read-only function parameter. This covers most of the programs under study. In Section 8.2.2, we compare the performance of this approach with that of our OSR-based approach that we described in Chapter 7.

8.1.2 General Dispatcher

We can extend Algorithm 2 to cover more cases of JIT value-based specialization. Algorithm 3 shows a more general dispatcher. Here, we have replaced the input parameter named *fef* in Algorithm 2 with V. The general dispatcher specializes the called function using the runtime values of V. We have also replaced the calls to function *replaceFevalCalls* and *getFunction* in Algorithm 2 with calls to function *transformIR* (line 5) and *makeKey* (line 9) in Algorithm 3 respectively.

1. Instead of using a wrapper, our future implementations will use a specialized compiler that directly performs the type conversion in the generated specialized version.

```
   input  : baseIR, V, inArgPtr, outArgPtr, cacheSlot
   output: void
 1 ci ← getCodeCacheInfo (baseIR, cacheSlot);
 2 entryPoint ← lookupFunction (ci, V);
 3 if entryPoint == NULL AND ci.counter <= THRESHOLD then
 4 |   newIR ← clone (baseIR);
 5 |   transformIR (newIR, V);
 6 |   llvmIR ← compileFunction (newIR, ci.argTypesStr);
 7 |   entryPoint ← compCallWrapper (llvmIR, newIR, ci.argTypesStr);
 8 |   // insert an entry for a new version into the cache;
 9 |   putNewVersion (ci, makeKey (V), entryPoint);
10 |   ci.counter ← ci.counter + 1;
11 end
12 if entryPoint ≠ NULL then
13 |   call entryPoint (inArgsPtr, outArgsPtr);
14 else
15 |   call ci.entryPoint(inArgsPtr, outArgsPtr);
16 end
```

Algorithm 3: A more general dispatch function

As an example of an application of the general dispatcher, consider the MATLAB `eval` (many dynamic languages have a similar feature as well). The MATLAB `eval` built-in evaluates MATLAB code given as its input string expression. Like the `feval` specialization, in some cases, we can also specialize a function with an `eval` call whose input string is a parameter of the function by developing a suitable *IR transformer* for the specialization.

Another example is the specialization of a function with a parameter that is an array. We can specialize the function using the properties of the array, such as array bounds, to generate more efficient code for loops that operate on such an array in the body of the function.

8.2 Experimental Results

We have described the implementation of our JIT value-based specialization approach. We shall now evaluate its performance over the existing McJIT with no `feval` call specialization. Later, we shall compare the performance of the JIT value-based specialization with the OSR-based specialization approach.

8.2.1 JIT value-based-specialization approach

The OSR-based approach (Section 7.2) is general-purpose, and can operate on any `feval` within a loop. However, our results show that there is still a gap between the performance of the OSR-approach and the upper bound. The value-specialization (Section 8.1) approach applies to a common case where the *fef* of the `feval` call is a read-only parameter of the enclosing function. In these cases the value-specialization can generate a completely specialized version of the function, without the need for run-time guards, and in which the JIT-time type and shape analysis can operate more accurately.

In Table 8.1, we show the results of the value-based specialization in a context where we can compare it to both the hand-coded, and OSR-based results. The column labelled **VB-specialization** gives the time and the speedup relative to the baseline. We note that this gives excellent results, with speedups approaching the hand-coded upper bound for all the benchmarks. The value-based results gave a geometric mean speedup of 3.22, which is

Benchmark	**Baseline**	**OSR-based (OPT0)**		**VB-Specialization**		**Hand-coded (D)**	
	t(s)	t(s)	speedup	t(s)	speedup	t(s)	speedup
bisect	2.38	1.93	1.23	1.66	1.43	1.68	1.42
newton	2.60	2.23	1.16	1.61	1.61	1.40	1.85
odeEuler	4.61	2.70	1.71	0.67	6.86	0.58	7.97
odeMidpt	7.10	4.22	1.68	0.83	8.53	0.67	10.56
odeRK4	12.79	7.35	1.74	0.89	14.30	0.68	18.88
gaussQuad	1.27	1.03	1.23	0.90	1.41	0.97	1.31
sim	3.47	3.40	1.02	2.60	1.33	2.51	1.38
Geometric Mean			1.37		3.22		3.58

Table 8.1 – Comparing Value-based specialization to OSR-based and hand-coded

substantially better than the 1.37 for the OSR-based approach, and almost as good as the upper bound of 3.58.

Under the JIT value-based specialization approach, the specialized versions of the functions with `feval` calls may no longer contain `feval` calls. Thus, allowing McJIT to generate much more efficient code. The *odeRK4* benchmark has four `feval` calls within a long-running loop. These calls are replaced with direct calls in the specialized version generated at run time. Because the `feval` target function (*fef*) is now known, the type inference engine can analyze the function more precisely, and McJIT can then generate more efficient code for both the target function and the calling function.

8.2.2 A comparison of the OSR-based and JIT value-based-specialization approaches

To understand in more detail why the value-based approach provides better performance, we need to examine the quality of the LLVM code generated for each benchmark, and the sources of overheads under the two approaches.

Under the OSR-based approach, McJIT generates less efficient code. This is so because McJIT generates a call to the interpreter for an `feval` call after *boxing* the arguments to the `feval` call to make them more generic. In addition, because the called function (*fef*)

at the call site is unknown during the compilation time, the type inference engine is unable to infer precise types for the values returned by the `feval` call, thus forcing the compiler to generate more generic instructions that are suitable for handling different types. This is a major source of inefficiency in the OSR-based approach.

Runtime guard computation can be expensive. The OSR-based approach generates runtime guards, which, as discussed in Section 7.2.5, depend on whether or not the arguments to an `feval` call have a fixed type. As mentioned in Section 7.3, for the three *ode* benchmarks, the type inference engine infers that the types to all the `feval` calls are variable, forcing the code transformer to generate an expensive guard for each `feval` call specialization.

We examined *odeRK4*. The code snippet for the only loop of the benchmark is shown in Listing 8.1.

Listing 8.1 – The *odeRK4* benchmark (from [Rec00a, Rec00b]).

```
1 for j=2:n
2     k1 = feval( diffeq , t(j-1),      y(j-1)           );
3     k2 = feval( diffeq , t(j-1)+h2, y(j-1)+h2*k1 );
4     k3 = feval( diffeq , t(j-1)+h2, y(j-1)+h2*k2 );
5     k4 = feval( diffeq , t(j-1)+h,  y(j-1)+h*k3  );
6     y(j) = y(j-1) + h6*(k1+k4) + h3*(k2+k3);
7 end
```

In the first `feval` call (line 2), the type inference engine infers that `t(j-1)` is a scalar floating point value. It, however, infers that `y(j-1)` can either be a scalar floating point value or a scalar complex value. In all the remaining three `feval` calls (lines 3 – 5), the type inference engine infers that the second parameter is a floating point value, but infers *unknown* for the third parameter.

Thus, in specializing the four `feval` calls in *odeRK4*, the code transformer inserts an expensive guard for each call specialization. The guards generated correspond to Row 2 of Table 7.1, that is, *f_cond* is evaluated at the function's entry basic block and *a_cond* is evaluated in the loop.

The JIT value-based approach is less affected by the foregoing issues. If all the `feval` calls in a function have the same *fef* and the *fef* is a read-only parameter of the function,

then the specialized code generated to match the *fef* at run time will not contain any `feval` call implementation. Each `feval` call in the AST of the function would have been replaced with a direct call to the *fef*. This allows the type inference engine to analyze the called function, which, in turn, allows McJIT to further specialize the call site and generate efficient code. The `feval` calls in all the benchmarks have their *fef*s passed in as a parameter, thus contributing to the generation of the more efficient code for the specialized versions.

It is, however, true that the JIT value-based approach incurs some runtime overheads, including that of the code cache look-up. But this is small given the expected gains. Further, unlike the OSR-based approach that is limited to specialization of `feval` calls within a long-running loop, the JIT value-based approach can specialize a function with an `feval` call that occurs anywhere within the body of the function.

We conclude that although the JIT value-based approach is less powerful than the OSR-based approach, it is more effective on our benchmark set. The JIT approach only works where the *fef* is passed as a read-only parameter to a function. It does not work if the *fef* is a local variable in the function with the `feval` call. The OSR-based approach works in all cases but incurs much larger runtime overhead. It is possible to combine the two approaches in a JIT compiler by first analyzing a function with an `feval` call to determine whether a call of the function can benefit from the JIT value-based specialization approach. With speedups of up to 14 times faster, it would seem that such techniques are well worth incorporating into JIT compilers for MATLAB and other dynamic languages which have compute-intensive solvers which are abstracted over the computation function (*fef*).

8.3 Summary

We introduced an effective JIT value-based specialization technique for optimizing `feval` calls, whose first argument is a function parameter. This is an alternative approach to the OSR-based on-the-fly mechanism for specializing `feval` calls in hot loops discussed in Chapter 7. We showed how the JIT value-based `feval` specialization can be extended to handle more cases of JIT value-based specialization in a MATLAB JIT compiler. The approach can also be used for JIT value-based specialization in other similar

dynamic languages as well. Indeed, the OSR-based approach can be similarly extended.

We collected a set of seven typical benchmarks that use `feval`, and demonstrated that our specialization approaches provide significant speedups over the base `feval` implementation for this benchmark set. In some cases the performance is near to the optimal performance of a hand-inlined function, but in other cases a gap remains. We would like to continue to develop new optimizations to further close that gap, and to apply the same sort of transformations to other dynamic features in MATLAB.

A somewhat surprising discovery in this work was the complex interplay between the JIT-time interprocedural type analysis and the on-the-fly transformations. The JIT value-based specialization can replace `feval` calls with direct calls in a function body, before doing the type analysis of that function body, thus leading to much better specialized code (because the interprocedural analysis can handle the direct calls much more precisely). On the other hand, this specialization can only happen at the function level, and only when the `feval` target function corresponds to a read-only parameter. The OSR-based method is more general, and can be applied at the level of loops, but suffers from less precise type information. It would be interesting to look at future work that combine the strengths of both approaches.

Chapter 9
Related Work

The work presented thus far in this thesis builds upon the strength of other work in the literature. Therefore, in this chapter, we present the work upon which this thesis has been developed. First, we discuss the work that are related to our array copy optimization approach. Second, we describe the work that are related to our OSR approach and show how our system is different from the past work on OSR. Third, we discuss the work related to our OSR-based dynamic inlining approach. Fourth, we review the past work related to our `feval` call specialization approach. We conclude the chapter with a review of the work related to our JIT value-based code specialization approach for functions with `feval` calls.

Before we present the related work, it is important to note that unlike dynamic optimization systems such as Dynamo [BDB00] that work on the native instruction stream, our transformations and optimizations are performed only at the intermediate-representation level.

9.1 Copy Optimization

Redundant copy elimination is a hard problem and implementations of languages such as Python [pyt12] are able to avoid copy elimination optimizations by providing multiple data structures: some with copy semantics and others with reference semantics. Programmers decide when to use mutable data structures. However, efficient implementations of languages like the MATLAB programming language that use copy semantics require copy

elimination optimization. The problem is similar to the aggregate update problem in functional languages [HB85, GH89, Ode91, Sas94, WC01]. To modify an aggregate in a strict functional language, a copy of the aggregate must be made. This is in contrast with the imperative programming languages where an aggregate may be modified multiple times.

APL [Ive62] is one of the oldest array-based languages. Weigang [Wei85] describes a range of optimizations for APL compiler, including a copy optimization that finds uses of a copy of a variable and replaces the copy with the original variable wherever possible. We implemented this optimization as part of our QuickCheck phase. We found the optimization effective at enabling the elimination of redundant copy statements by the dead-code optimizer. However, this optimization is unable to eliminate redundant copies of arguments and return values. Hudak and Bloss [HB85] use an approach based on abstract interpretation and conventional flow analysis to detect cases where an aggregate may be modified in place. Their method combines static analysis and dynamic techniques. It involves a rearrangement of the execution order or an optimized version of reference counting, where the static analysis fails. Our approach is based on flow analysis but we do not change the execution order of a program.

The interprocedural aliasing and side-effect problem [Muc97] is related to the copy elimination problem. By using call by reference semantics, when an argument is passed to a function during a call, the parameter becomes an alias for the argument in the caller and if the argument contains an array reference, the referenced array becomes a shared array; any updates via the parameter in the callee updates the same array referenced by the corresponding argument in the caller. Without performing a separate and expensive flow analysis, our approach easily detects aliasing and side effects in functions. Wand and Clinger present [WC01] interprocedural flow analyses for aliasing and liveness based on set constraints. They present two operational semantics: the first one permits destructive updates of arrays while the other does not. They also define a transformation from a strict functional language to a language that allows destructive updates. Like Wand and Clinger, our approach combines liveness analysis with flow analysis. Unlike Wand and Clinger, however, our analyses are intraprocedural and have been implemented in a JIT compiler for an imperative language.

The work of Goyal and Paige [GP98] on copy optimization for SETL [SDSD86] is particularly interesting. Their approach combines a RC scheme with static analysis. A combination of must-alias and live-variable analyses is used to identify dead variables and the program points where a statement that redefines a dead variable can be inserted to facilitate destructive updates. Like our approach, this technique is capable of eliminating the redundant copying of a shared location that can occur during an update of the location; however, it is different from our approach. In particular, it generates dynamic checks to detect when to create copies. As mentioned in Section 3.7, our approach rarely generates dynamic checks.

9.2 On-Stack Replacement

Hölzle et al. [HCU92] used an OSR technique to dynamically de-optimize running optimized code to debug the executing program. OSR techniques have been in used in several implementations of Java programming language, including Jikes research VM [FQ03, AAB+05] and HotSpot [PVC01] to support adaptive recompilation of running programs. A more general-purpose approach to OSR for the Jikes VM was suggested by Soman and Krintz [SK06] which decouples OSR from the program code. Our approach is more similar to the original Jikes approach in that we also implement OSR points via explicit instrumentation and OSR points in the code. However, we have designed our OSR points and OSR triggering mechanism to fit naturally into the SSA-form LLVM IR and tool set. Moreover, the LLVM IR is entirely different from Java byte-code and presents new challenges to OSR implementation at the IR level (Section 4.3). Our approach is also general-purpose in the sense that the OSR can potentially trigger any optimization or de-optimization that can be expressed as an LLVM transform.

Recently, Süsskraut et al. [SKW+10] developed a tool in LLVM for making a transition from a slow version of a running function to a fast version. Like Süsskraut et al., our system is based on LLVM. However, there are significant differences in the approaches. While their system creates two versions of the same function statically, and transitions from one version to another at run time, our proposed solution instruments and recompiles code

dynamically at run time. This is more suitable for an adaptive JIT. Secondly, the approach used by Süsskraut et al. stores the values of local variables in a specially allocated area that is always accessible when an old stack frame is destroyed and a new stack frame is created for the executing function. This requires a special memory management facility beyond that provided by LLVM. In contrast to their approach, our approach does not require a special allocation because the stack frame is not destroyed until OSR transition is completed. The recursive call of the executing function essentially extends the old stack frame. We only have to copy the old addresses and scalar values from the old stack frame onto the new stack frame. Finally, another notable difference between our approach and that taken by Süsskraut et al. is that their approach requires instrumenting the caller to support OSR in a called function. This may result in high instrumentation overhead. In our approach, we do not instrument a caller to support OSR in a callee.

OSR has been implemented in several virtual machines for JavaScript. Like the Jikes virtual machine, V8 VM [V8V13] and JavaScriptCore [Jav13] allow transitions to a more optimized version of a running function and de-optimization to the original version. In our approach, we allow transitions to a more optimized version and de-optimization to the last version of the less optimized code. In contrast to these systems, our OSR technique supports a transition from optimize code to more optimized code.

9.3 Selective Dynamic Inlining

Inlining is an important compiler optimization. It has been used successfully in many production compilers, especially compilers for object-oriented programming languages. Several techniques for effective inlining were introduced in the several implementations of SELF [CU91, HU94]. SELF-93 [HU94] uses heuristics to determine the root method for recompilation by traversing the call stack. It then in-lines the traversed call stack into the root method. The HotSpot Server VM [PVC01] uses a similar inlining strategy.

Online profile-directed inlining has been explored in many VMs [CLS00, AFG+00, AHR02, SYN02, ATBC+03, HG03]. The Jikes research VM [AAB+05] considers the effect of inlining in its cost-benefit model for recompilation by raising the expected benefit of

recompiling a method with a frequently executed call site. Suganuma et al. report that for inlining decisions for non-tiny methods, heuristics based solely on online profile data outperforms those based on offline, static data [SYN02]. Hazelwood and Grove [HG03] suggest using a combination of profiling data with context sensitivity to guide inlining decisions. They recorded a good reduction in compilation time and code space.

In our approach, like the HotSpot server compiler [PVC01], we use an iteration counter to detect long-running loops and consider calls to small functions occurring in those loops as good inlining candidates. Further, calls to functions with a symbol environment set-up code are also considered for inlining, provided that the calling function has a symbol environment associated with it.

Online profile-directed inlining in a MATLAB compiler has not been reported in the literature. We expect that by using online profiling information to identify hot call sites and guide inlining decisions, inlining of the most critical call sites will boost performance.

9.4 OSR-Based `feval` Specialization

Historically, function dispatch in dynamic languages was implemented with a dispatch look-up table. This was found to be slow. More efficient approaches have emerged; they often employ a variety of caching techniques to speed up table look up. Smalltalk-80 [GR85, Kra83] uses a global cache to improve look up performance.

Our OSR-based approach is more related to the inline caching [DS84b] approach used in another Smalltalk implementation. Interestingly, the Smalltalk implementation was based on several studies of Smalltalk programs that revealed that 95% of the time, the type of a Smalltalk message receiver is constant [DS84b, UP87, Ung87]. Our approaches to `feval` optimization are also based on the observation that `feval` calls in most MATLAB loops have unchanging first argument.

The inline caching technique used in the Smalltalk compiler involves caching the address of a looked-up method at the call site by modifying the compiled target code on-the-fly — by overwriting the call instruction. This allows the method to be called directly in

a subsequent execution, avoiding the need for a look up. It also involves generating additional code (often called prologue) in the method that tests that the receiver type is correct before executing the body of the method. However, if the test does not succeed, it calls the look-up code.

Hölzle et al. extended the inline caching technique to handle polymorphic call sites by including more than one cached look-up result per call site. This technique is known as polymorphic inline caching (PIC) [HCU91]. The PIC approach caches all the receiver types at a call site in a *stub* that is generated on-the-fly and rebinds the call to the stub routine.

In contrast to these approaches, our implementation is done completely at the LLVM-IR level, and not at target code level. Without on-stack replacement support [HCU92, PVC01, FQ03, AAB+05, SK06, LH13, Lam12], it is hard to cache previous function look-up result "inline" (i.e., at the call site). We also do not need additional code in the called function. We insert runtime guards so that execution can continue with the original call to the dispatcher if the guard fails. Also our backup path obviates the need to cache look-up results in a stub as in the PIC case used in the implementations of SELF [CU91, HU94].

Although multi-paradigm programming languages such as Python, JavaScript, and functional languages, including Lisp, Haskell, Scheme support higher-order functions, the function arguments are directly evaluated at run time and often lead to runtime code generation that is typically supported by polymorphic type inference, and sometimes, binding time analysis [NN91]. The MATLAB `feval` is an overloaded built-in that accepts a function name as a string or function handle and indirectly evaluates, at run time, the function argument. Our approaches are supported by a type-inference analysis, although it is explicit that the `feval` built-in evaluates functions only. Our approaches are aimed at improving JIT compiled code, and facilitating efficient compilation of the MATLAB `feval`, which can be extended to handle similar features in other dynamic languages, where it would have otherwise appeared impossible.

To the best of our knowledge, we are not aware of any work on optimization technique for `feval` in a JIT compiler for MATLAB.

9.5 JIT Value-Based Specialization

In a SELF [Cha92] compiler, Chambers and Ungar [CU89] customize the method called at a call site to a specific *receiver* type. SELF is a pure object-oriented programming language. Like Chambers and Ungar, Chevalier-Boisvert et al. customize a called function at a call site in the McVM JIT compiler [CBHV10]. They, however, based their customization on the set of inferred types for *all* the arguments to the called function at the call site. Our JIT value-based specialization approach to `feval` call optimization in the McVM JIT compiler extends this type specialization further with a customization based on the runtime value of an argument that corresponds to a target function of an `feval` call in the called function.

Systems such as *tcc* [PEK97], *Tempo* [CHM+98], *Dyc* [GMP+00] use annotations to express code on which dynamic compilation should be performed. Muth et al. [MWD00] use profiling and runtime guards to determine when specialized code should be used. In our case, we neither use user-level annotations to mark code region nor profile the runtime values of variables that can reference a function that is a target of an `feval` call. Rather, we replace a call to the version of the called function that is already specialized to a fixed set of argument types (*the initial version*) with a call to a generic dispatch function. At run time, we generate a specialized version of the called function using the value passed in to the parameter that is a target of an `feval` call within the function. We use a small look-up table to cache or select the correct version to dispatch at run time. If the value varies frequently, we stop generating new versions and instead start executing the initial version.

The use of templates to reduce runtime code generation overhead has been thoroughly investigated [CN96, CHM+98, APC+96, CEA+95]. Templates are sequence of instructions with *holes* in place of some values [LL96]. We explored the use of templates to reduce runtime code generation overhead at the LLVM IR level.

If, instead of using the AST, we can generate an LLVM-code template for a function with an `feval` call whose target function is a parameter, we can significantly reduce the cost of generating the LLVM code for a specialized version at run time. We can achieve this by simply copying the template and replacing the *hole* in the copy with the known value of the parameter corresponding to the target function of the `feval` call.

For our implementation, however, we found that generating an efficient template ahead of time is often not possible. This is because the name, and therefore, the precise types of the return values of a function that is a target of an `feval` call are generally unknown at that time. This causes the compiler to generate generic code that can handle different types for the operations that depend on those values after the call. The code generated at run time from the AST benefits greatly from the type information produced by the type-inference engine after it has analyzed the now known target of an `feval` call and the caller as well.

It is possible, using partial evaluation [JGS93] techniques similar to that used in the *FABIUS* compiler [LL96], to generate ahead of time specialized versions of a function with an `feval` call whose target function is a parameter, provided that some values of the `feval` target function can be determined ahead of time. We do not use this approach because it can lead to a large increase in compilation time and the creation of code that is never executed.

Chapter 10
Conclusions and Future Work

We discussed several compilation and performance challenges for a MATLAB JIT compiler, and presented a collection of novel techniques that address the challenges. Our techniques use runtime information about program behaviour to support on-the-fly program transformations and optimizations in a JIT compiler for the MATLAB language. Some of the techniques are supported by our new JIT-time static flow analyses.

Throughout the thesis, we demonstrated through experiments that measured different aspects of our approaches. We found that our techniques can be used to obtain good performance in a JIT compiler for the MATLAB language and other similar dynamic languages.

We discussed an approach to using JIT-time static analyses to enable an efficient implementation of array copy semantics in a MATLAB JIT compiler. We developed four JIT-time static analyses to support a staged approach to copy optimization. The first stage is supported by two fast and effective analyses, and the second stage is supported by *Necessary Copy* and *Copy Placement* analyses. We found that this approach generates as many copies as the reference-counting approach and with no runtime check.

As we have explained, on-the-fly transformations and optimizations often require on-stack replacement, but implementing on-stack replacement can be very challenging. We proposed, designed and developed a modular approach to implementing on-stack replacement that can easily be added to a JIT compiler developed in LLVM, without the need to re-build the underlying LLVM libraries. This was an important step towards the realization of the on-the-fly techniques presented in this thesis. We showed, using a case study, how

our OSR approach can be used to support selective dynamic inlining of hot call sites in long-running loops. We also presented how to leverage the OSR implementation to support other on-the-fly optimizations such as the *`feval` call specialization*.

We demonstrated that dynamic function evaluation via MATLAB `feval` can cause significant overheads in interpreters and JIT compilers. We presented two new techniques for optimizing such `feval` calls. We explained the first mechanism, which uses OSR to specialize `feval` calls in long-running loops, and gave evidence to show that this technique can lead to significant performance gains. We also described and discussed the second mechanism, which is less general but more effective than the first approach. It specializes a function with an `feval` call whose target function is a parameter of the function. It uses the argument passed into the parameter for the specialization. We found this particular technique to be highly effective on our benchmark set.

We compared the OSR-based approach with JIT value-based approach and found that the latter is much more effective than the former. The JIT value-based approach can transform an `feval` call located anywhere within a function provided that the target function of the `feval` call is a read-only parameter of the enclosing function. It benefits much from the more precise runtime-type information that McJIT uses to generate more efficient code at run time. The OSR-based approach, however, can transform an `feval` call located within a loop body whether or not the target function is a read-only parameter of the function, but suffers from less precise type information.

The ideas presented in this thesis have been influenced mainly by many research work in object-oriented languages — both static and dynamic. We reviewed the literature and presented the main work related to ours. For MATLAB, we are not aware of any work on on-the-fly transformations and optimizations for a MATLAB JIT compiler. Thus, our research work is the first in this area, and we hope that our work will inspire other researchers as well.

We implemented OSR for the LLVM JIT compiler toolkit. Our copy optimization and `feval` call specialization techniques have been implemented in McJIT. Our implementation is available as open source software.

10.1 Future Work

Here, we highlight the direction for the future work of the research presented in this thesis.

Copy Optimization: The copy optimization [LH11] works on shared arrays. If an update is made to a shared array, the whole array is copied. This works well for one-dimensional arrays. However, if the array is multi-dimensional, the whole array will still be copied even when the update affects a location in one of the dimensions only. It would be nice to extend our copy optimization approach to allow sharing of arrays based on array dimensions. This will reduce the amount of data copied when a shared array is updated.

On-stack replacement: Our current approach to on-stack replacement assumes that the application is single-threaded. This is sufficient for our JIT compiler for the MATLAB programming language and other similar languages. To be more useful to the larger programming language and virtual machine communities, however, it would be nice to extend our approach with the capability of handling multi-threaded applications.

`feval` call specialization: We discussed the strengths and limitations of both the OSR-based and JIT value-based approaches to specializing `feval` calls in long-running loops. We believe that these two approaches can be combined and extended to support more runtime value-based specializations in JIT compilers for dynamic languages, in particular, for the MATLAB language.

As we mentioned in Chapter 7, one interesting area of further optimization is MATLAB `eval`. MATLAB `eval` is more general than MATLAB `feval`; it can evaluate MATLAB code in a string expression. An analysis of this string can reveal certain patterns of usage common to MATLAB programs, which can provide opportunities for specialization in some cases. Indeed, for a MATLAB JIT compiler, more interesting value-based specializations can be performed using loop and array properties, such as loop and array bounds.

McJIT's type inference engine [CBHV10] has some limitations. One of which is its inability to propagate array shape information. By enhancing the type inference engine with the capability to infer array shape information, more loop-based on-the-fly transformations and optimizations that use array shape information can be developed.

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Appendix A
Relevant McVM compilation flags

Here we present McVM flags related to the work presented in this thesis.

```
./mcvm -jit_enable true -jit_osr_enable true
       -jit_osr_strategy outer
```

-jit_enable: Enables JIT compilation in McVM. The default execution engine is the interpreter. If the flag is set to *true*, JIT compilation is used, otherwise, all code will be interpreted.

-jit_osr_enable: Enables OSR if JIT compilation is enabled. It is set to *false* by default.

-jit_osr_strategy: If OSR is enabled, it uses the strategy specified. Another valid option is *inner*, which is used to specify that McJIT should insert OSR point in the inner-most loop of a loop nest. If the specified strategy is *outer*, McJIT will insert OSR points in the appropriate outer-most loops.

-jit_osr_inline: To force dynamic inlining, if OSR is enabled.

Appendix B
Copy optimization aspect

In this section, we list the *aspect* used in estimating the number of copies a MATLAB program would perform under the reference-counting approach for implementing array copy semantics in MATLAB system.

```
1
2  aspect  refcounter
3
4  % This aspect counts the number of copies generated
5  % in a matlab program, using the matlab copy semantics:
6  % 'copy on write '.
7  % Only copies generated in program functions are
8  % considered. Built-in functions may generate further
9  % copies. However, such copies are not counted since
10 % aspectMatlab compiler (amc) can not profile
11 % built-in functions.
12 %
13 % Limitations: For accurate result only one user-defined
14 %              function may be used as a rhs of an
15 %              assignment statement. Complicated expressions
16 %              involving multiple user-defined functions
17 %              should be split into 'simple forms'.
18 %              However, this does not affect built-ins and
19 %              matlab-defined m-files.
20 %
21 % Date: February 2010.
22 % Author: Nurudeen Lameed
23 % Email: nlamee@cs.mcgill.ca
24
25  properties
26 verbose_ = 0;                % # display progress
27 matlab_builtin_home_ = '/packages/matlab'; % for builtin
28 defs_count_ = 0;              % # of definitions
29 writes_count_ = 0;            % # of array writes
30 num_copies_ = 0;              % # of copies generated
31 m_ID_gen_ = 0;                % # unique mem_ory id generator
32 top_ = 0;                     % top_ of stack_ pointer
33 mem_ = struct();              % mem_ory
34 stack_ = {};                  % array of stack_ frames
35
36 % for the current callee
37 last_assign_line_ = -1;
38 multi_assign_on_ = 0;
39 arg_names_ = {};              % temp for arg_names_
40 param_write_off_ = 0;         % flag for setting params
41 end
42
43 methods
44 function push(this, s)
45  this.top_ = this.top_ + 1;
46  this.stack_{this.top_} = s;
47 end
48
49 function s = pop(this)
50 s = this.stack_{this.top_};
```

```
51  this.top_ = this.top_ - 1;
52  end
53
54  function retVal = isDefFromFunc(this, line)
55  retVal = 0;
56  if (isfield(this.stack_{this.top_}, 'last_call_addr_'))
57      lastCallAddr = getfield(this.stack_{this.top_}, ...
58          'last_call_addr_');
59      if (lastCallAddr == line)
60          retVal = 1;
61      end
62  end
63  end
64
65  function incrDefsCount(this)
66  this.defs_count_ = this.defs_count_ + 1;
67  end
68
69  function genMem_(this, name)
70  %generate a new mem_ory space for this name
71
72  this.m_ID_gen_ = this.m_ID_gen_ + 1;
73  mID = ['m', num2str(this.m_ID_gen_)];
74  this.mem_ = setfield(this.mem_, mID, 1);
75
76  % update the current stack_ frame
77  this.stack_{this.top_} = setfield(this.stack_{this.top_}, name, mID);
78  end
79
80  function incrRefCount(this, mID)
81  rc = getfield(this.mem_, mID);
82  this.mem_ = setfield(this.mem_, mID, rc + 1);
83  end
84
85  function decrRefCount(this, mID)
86  rc = getfield(this.mem_, mID);
87  if ((rc - 1) == 0)   % garbage ?
88      this.mem_ = rmfield(this.mem_, mID);
89  else
90      this.mem_ = setfield(this.mem_, mID, rc - 1);
91  end
92  end
93
94  function incrCpCount(this, loc, name, line)
95  % increment the number of copies
96
97  % find the mem_ory referenced by this symbol
98  mID = getfield(this.stack_{this.top_}, name);
99
100 %disp(['memory = ', mID, ' symbol = ', name]);
101 %disp(this.mem_);
```

```
102 %disp(this.stack_{this.top_});
103 % get the reference count for the object referenced
104 rc = getfield(this.mem_, mID);
105
106 if (rc > 1) %perform copy
107     if (this.verbose_)
108         disp(['ARRAY COPY:: (name, line) : (', name, ',', ...
109             num2str(line), ')']);
110     end
111     this.num_copies_ = this.num_copies_ + 1;
112     this.genMem_(name);
113
114     % update ref count
115     this.mem_ = setfield(this.mem_, mID, rc - 1);
116 end
117 this.incrWritesCount();
118 end
119
120 function incrWritesCount(this)
121 this.writes_count_ = this.writes_count_ + 1;
122 end
123
124 function init(this)
125 this.verbose_ = 1;
126 this.matlab_builtin_home_ = '/packages/matlab'
127 this.defs_count_ = 0;
128 this.writes_count_ = 0;
129 this.num_copies_ = 0;
130 this.m_ID_gen_ = 0;
131 this.top_ = 0;
132 this.mem_ = struct();
133 this.stack_ = {};
134
135 % for the current callee
136 this.last_assign_line_ = -1;
137 this.multi_assign_on_ = 0;
138 this.arg_names_ = {};
139 this.param_write_off_ = 0;
140 end
141
142 function printStatistics(this, name)
143 disp(['Result for ', name]);
144 disp('=======================================');
145 disp(['Array-definition count: ', num2str(this.defs_count_)]);
146 disp(['Array-write count: ', num2str(this.writes_count_)]);
147 disp(['Total number of copies generated: ', num2str(this.num_copies_)]);
148
149 %         if (this.verbose_)
150 %     disp('Mem_ory dump');
151 % disp(this.mem_);
152 % end
```

```
153 end
154
155 function insertDef(this, loc, lhs, rhs)
156 tmp = [];
157
158 % is it a redefinition ?
159 if (isfield(this.stack_{this.top_}, lhs))
160     tmp = getfield(this.stack_{this.top_}, lhs);
161 end
162
163 %locate the rhs from the current stack_
164 if (isfield(this.stack_{this.top_}, rhs)) %found
165
166     % get the mem_ory for the rhs
167     mID = getfield(this.stack_{this.top_}, rhs);
168
169     % test for a redundant assignment
170     if (¬isequal(mID, tmp))
171
172         this.stack_{this.top_} = setfield(this.stack_{this.top_},lhs, mID);
173
174         % incr the mem_ory ref count
175         this.incrRefCount(mID);
176         if (¬isequal(tmp,[]))
177             this.decrRefCount(tmp);
178         end
179     end
180 else
181     this.genMem_(lhs);
182     if (¬isequal(tmp,[]))
183         this.decrRefCount(tmp);
184     end
185 end
186 this.incrDefsCount();
187 end
188 end
189
190 patterns
191 allDefs: set(*);   % match all defs
192 aWrites: set(*(..));     % match any array write
193 aDefsOnly: set(*) & (¬ set(*(..)));   % match any array def only
194 callMain: execution(rctest);
195 callMain2: execution(rctest2);
196 callMain3: execution(rctest3);
197 callMain4: execution(rctest4);
198 funcExec: execution(*); % match any func execution
199 funcCall: call(*); % match any function call
200
201 % begin benchmarks
202 callTRID: call(trid_test);
203 execTRID: execution(trid_test);
```

```
204
205 callADPT: call(adpt_test);
206 execADPT: execution(adpt_test);
207
208 callCAPR: call(capr_test);
209 execCAPR: execution(capr_test);
210
211 callCLOS: call(clos_test);
212 execCLOS: execution(clos_test);
213
214 callCRNI: call(crni_test);
215 execCRNI: execution(crni_test);
216
217 callDICH: call(dich_test);
218 execDICH: execution(dich_test);
219
220 callDIFF: call(diff_test);
221 execDIFF: execution(diff_test);
222
223 callFDTD: call(fdtd_test);
224 execFDTD: execution(fdtd_test);
225
226 callFFT: call(fft_test);
227 execFFT: execution(fft_test);
228
229 callFIFF: call(fiff_test);
230 execFIFF: execution(fiff_test);
231
232 callMBRT: call(mbrt_test);
233 execMBRT: execution(mbrt_test);
234
235 callNB1D: call(nb1d_test);
236 execNB1D: execution(nb1d_test);
237
238 callNB3D: call(nb3d_test);
239 execNB3D: execution(nb3d_test);
240
241 callNFRC: call(nfrc_test);
242 execNFRC: execution(nfrc_test);
243 % end benchmarks
244 end
245
246 actions
247
248 afterAllDefs: after allDefs:(loc, name, aobj, line)
249 if (this.last_assign_line_ == line && ¬this.param_write_off_)
250
251     % multiple assignment detected
252     if (this.verbose_)
253         disp(['multiple assignment in line ', num2str(line), ...
254             ' lhs: ', name, ' position: ', ...
```

```
255                 num2str(this.multi_assign_on_ + 2)]);
256         end
257
258         if (this.multi_assign_on_)
259             this.multi_assign_on_ = this.multi_assign_on_ + 1;
260         else
261             this.multi_assign_on_ = 1;
262         end
263     else
264         this.last_assign_line_ = line;
265         this.multi_assign_on_ = 0;
266     end
267 end
268
269 afterDefsAct: after aDefsOnly: (loc, name, aobj, line)
270 if (this.verbose_)
271     disp(['DEF:: (name, line) : (', name, ',', num2str(line), ')', ...
272         ' = ', aobj]);
273 end
274 if (this.param_write_off_)
275     this.param_write_off_ = this.param_write_off_ - 1;
276 elseif (this.isDefFromFunc(line))
277     retCount = getfield(this.stack_{this.top_}, ...
278         'ret_cnt_');
279     retValIndex = this.multi_assign_on_ + 1;
280     if (retValIndex <= retCount)
281         if (isfield(this.stack_{this.top_}, name))
282             tmp = getfield(this.stack_{this.top_}, name);
283             this.decrRefCount(tmp);
284         end
285         retvar = ['ret_val_', num2str(retValIndex)];
286         %disp(['ret val = ', retvar]);
287         mID = getfield(this.stack_{this.top_}, retvar);
288         this.stack_{this.top_} = setfield(this.stack_{this.top_}, ...
289             name, mID);
290     end
291 else
292     this.insertDef(loc, name, aobj);
293 end
294 end
295
296 afterAWriteAct: after aWrites: (loc, name, line)
297 if (this.verbose_)
298     disp(['ARRAY WRITE:: (name, line) : (', name, ',', ...
299         num2str(line), ')']);
300 end
301 if isfield(this.stack_{this.top_}, name) % undefined?
302     this.incrCpCount(loc, name, line);
303 else
304     this.genMem_(name);       % define ...
305 end
```

```
306 end
307
308
309 beforeFuncCallAct: before funcCall: (name, args, line, ainput)
310 val = line;
311 if (exist(name, 'builtin') | strfind(which(name), ...
312     this.matlab_builtin_home_))
313     val = -1;
314 end
315
316 this.stack_{this.top_} = setfield(this.stack_{this.top_}, ...
317     'last_call_addr_', val);
318
319 % set the call arg names
320 this.arg_names_ = ainput;
321 end
322
323 afterFuncCallAct: after funcCall: (name, args, line) ...
324     % do some stack_ clean up task
325 end
326
327 beforeFuncExecAct: before funcExec: (name, ainput, args, line)
328 %               disp(this.mem_);
329 if numel(ainput) ~= numel(this.arg_names_)
330     disp([name, ':: error: # of args (', ...
331         num2str(numel(ainput)), ...
332         ' != # of parameters (', num2str(numel(this.arg_names_))]);
333     exit;
334 end
335
336 if (this.verbose_)
337     disp(['pushing a new stack_ frame for ', name]);
338 end
339 % create a stack_ frame for the function
340 this.push(struct());
341
342 %process args -> params transition
343 for i=1:numel(this.arg_names_)
344     if (isempty(this.arg_names_{i}))
345
346         % generate a new memory for the parameter
347         this.genMem_(ainput{i});
348     else
349         %disp(['Arg name ', this.arg_names_{i}])
350         mID = getfield(this.stack_{this.top_ - 1}, this.arg_names_{i});
351         this.stack_{this.top_} = ...
352             setfield(this.stack_{this.top_}, ainput{i}, mID);
353         this.incrRefCount(mID);
354     end
355 end
356
```

```
357 % parameter writing off
358  this.param_write_off_ = numel(this.arg_names_);
359
360 end
361
362 afterFuncExecAct: after funcExec: (loc, name, aoutput, ...
363     line)
364  if (this.verbose_)
365     disp(['popping the stack_ frame for ', name]);
366 end
367 sframe = this.pop();
368  if (this.top_ > 0)
369
370     % add a return values count to the callers stack_ frame
371      this.stack_{this.top_} = ...
372           setfield (this.stack_{this.top_}, 'ret_cnt_', ...
373          numel(aoutput));
374     for j=1:numel(aoutput)
375          mID = getfield(sframe, aoutput{j});
376          retvar = ['ret_val_', num2str(j)];
377
378          % copy ret val to the caller's stack_
379          this.stack_{this.top_} = ...
380               setfield (this.stack_{this.top_}, retvar, mID);
381          this.incrRefCount(mID);
382     end
383 end
384
385  if (isfield(sframe, 'last_call_addr_'))
386     sframe = rmfield(sframe, 'last_call_addr_');
387 end
388
389  if (isfield(sframe, 'ret_cnt_'))
390     sframe = rmfield(sframe, 'ret_cnt_');
391 end
392
393  fields = fieldnames(sframe);
394 for i=1:numel(fields)
395     if (strfind(fields{i}, 'ret_val_') > 0)
396          continue;     %skip it
397     end
398
399     % get the memory ID
400     mID = getfield(sframe, fields{i});
401      this.decrRefCount(mID);
402 end
403
404  if (this.verbose_)
405     disp(['final stack_ frame for ', name, ':']);
406     disp(sframe);
407     disp(['caller''s stack_ frame for ', name, ':']);
```

```
408         if ( this .top_ > 0)
409             disp( this .stack_{ this .top_});
410         end
411         disp('Memory dump');
412         disp( this .mem_);
413     end
414     end
415
416     afterMainCallAct: after callMain: (name)
417      this . printStatistics (name);
418     end
419     afterMainCall2Act: after callMain2: (name)
420      this . printStatistics (name);
421     end
422     afterMainCall3Act: after callMain3: (name)
423      this . printStatistics (name);
424     end
425     afterMainCall4Act: after callMain4: (name)
426      this . printStatistics (name);
427     end
428
429     % print result for benchmarks
430     beforeCallADPT: before callADPT
431      this . init ();
432     end
433     afterExecADPT: after execADPT: (name)
434      this . printStatistics (name);
435     end
436
437     beforeCallCAPR: before callCAPR
438      this . init ();
439     end
440     afterExecCAPR: after execCAPR: (name)
441      this . printStatistics (name);
442     end
443
444     beforeCallCLOS: before callCLOS
445      this . init ();
446     end
447     afterExecCLOS: after execCLOS: (name);
448      this . printStatistics (name);
449     end
450
451     beforeCallCRNI: before callCRNI
452      this . init ();
453     end
454     afterExecCRNI: after execCRNI: (name)
455      this . printStatistics (name);
456     end
457
458     beforeCallDICH: before callDICH
```

```
459  this . init ();
460 end
461 afterExecDICH: after execDICH: (name)
462  this . printStatistics (name)
463 end
464
465 beforeCallDIFF: before callDIFF
466  this . init ();
467 end
468 afterExecDIFF: after execDIFF: (name)
469  this . printStatistics (name);
470 end
471
472 beforeCallFDTD: before callFDTD
473  this . init ();
474 end
475 afterExecFDTD: after execFDTD: (name)
476  this . printStatistics (name);
477 end
478
479 beforeCallFFT: before callFFT
480  this . init ();
481 end
482 afterExecFFT: after execFFT: (name)
483  this . printStatistics (name);
484 end
485
486 beforeCallFIFF: before callFIFF
487  this . init ();
488 end
489 afterExecFIFF: after execFIFF: (name)
490  this . printStatistics (name)
491 end
492
493 beforeCallMBRT: before callMBRT
494  this . init ();
495 end
496 afterExecMBRT: after execMBRT: (name)
497  this . printStatistics (name);
498 end
499
500 beforeCallNB1D: before callNB1D
501  this . init ();
502 end
503 afterExecNB1D: after execNB1D: (name)
504  this . printStatistics (name);
505 end
506
507 beforeCallNB3D: before callNB3D
508  this . init ();
509 end
```

```
510 afterExecNB3D: after  execNB3D: (name)
511  this .  printStatistics  (name);
512 end
513
514 beforeCallNFRC: before  callNFRC
515  this . init ();
516 end
517 afterExecNFRC: after  execNFRC: (name)
518  this .  printStatistics  (name);
519 end
520
521 beforeCallTRID: before  callTRID :  (name)
522  this . init ();
523 end
524
525 afterExecTRID:  after  execTRID: (name)
526  this .  printStatistics  (name);
527 end
528 % end benchmark
529 end
530 end
```