
WRL Technical Note TN-18



Predicting Program Behavior Using Real or Estimated Profiles

David W. Wall

The Western Research Laboratory (WRL) is a computer systems research group that was founded by Digital Equipment Corporation in 1982. Our focus is computer science research relevant to the design and application of high performance scientific computers. We test our ideas by designing, building, and using real systems. The systems we build are research prototypes; they are not intended to become products.

There is a second research laboratory located in Palo Alto, the Systems Research Center (SRC). Other Digital research groups are located in Paris (PRL) and in Cambridge, Massachusetts (CRL).

Our research is directed towards mainstream high-performance computer systems. Our prototypes are intended to foreshadow the future computing environments used by many Digital customers. The long-term goal of WRL is to aid and accelerate the development of high-performance uni- and multi-processors. The research projects within WRL will address various aspects of high-performance computing.

We believe that significant advances in computer systems do not come from any single technological advance. Technologies, both hardware and software, do not all advance at the same pace. System design is the art of composing systems which use each level of technology in an appropriate balance. A major advance in overall system performance will require reexamination of all aspects of the system.

We do work in the design, fabrication and packaging of hardware; language processing and scaling issues in system software design; and the exploration of new applications areas that are opening up with the advent of higher performance systems. Researchers at WRL cooperate closely and move freely among the various levels of system design. This allows us to explore a wide range of tradeoffs to meet system goals.

We publish the results of our work in a variety of journals, conferences, research reports, and technical notes. This document is a technical note. We use this form for rapid distribution of technical material. Usually this represents research in progress. Research reports are normally accounts of completed research and may include material from earlier technical notes.

Research reports and technical notes may be ordered from us. You may mail your order to:

Technical Report Distribution
DEC Western Research Laboratory, UCO-4
100 Hamilton Avenue
Palo Alto, California 94301 USA

Reports and notes may also be ordered by electronic mail. Use one of the following addresses:

Digital E-net:	DECWRL : WRL-TECHREPORTS
DARPA Internet:	WRL-Techreports@decwrl.dec.com
CSnet:	WRL-Techreports@decwrl.dec.com
UUCP:	decwrl!wrl-techreports

To obtain more details on ordering by electronic mail, send a message to one of these addresses with the word "help" in the Subject line; you will receive detailed instructions.

Predicting Program Behavior Using Real or Estimated Profiles

David W. Wall

December, 1990



Western Research Laboratory 100 Hamilton Avenue Palo Alto, California 94301 USA

Abstract

There is a growing interest in optimizations that depend on or benefit from an execution profile that tells where time is spent. How well does a profile from one run describe the behavior of a different run, and how does this compare with the behavior predicted statically by examining the program itself? This paper defines two abstract measures of how well a profile predicts actual behavior. According to these measures, real profiles indeed do better than estimated profiles, usually. A perfect profile from an earlier run with the same data set, however, does better still, sometimes by a factor of two. Using such a profile is unrealistic, and can lead to inflated expectations of a profile-driven optimization.

1. Introduction

Many people have built or speculated on systems that use a run-time profile to guide code optimization. Applications include the selection of variables to promote to registers [7,8], placement of code sequences to improve cache behavior [3,6], and prediction of common control paths for optimizations across basic block boundaries [2,5].

When such work is presented, two questions are often asked but seldom adequately answered. How well does a profile from one run predict the behavior of another? And how well can you do with an estimated profile derived from static analysis of the program? It is important to answer these questions in general terms as well as specific. A profile from a different run may be very useful for one kind of optimization but nearly useless for another kind. The optimization may require identifying the specific program entities that are most used, or it may require only identifying some that are used a lot.

This paper describes a study of how well an estimated profile predicts real behavior, and how well a profile from one run predicts the behavior of another run.

2. Methodology.

The *pixie* tool from Mips [4] instruments an executable file with basic block counting; when the instrumented program is run, it produces a table telling how many times each basic block was executed. From this table, in combination with static information from the executable file, we derive four kinds of profiles. The first is the *basic block* profile, which is just the mapping from each basic block to its execution count. The second is the *procedure* profile, which maps each procedure to the number of times it is entered. The third is the *call* profile, which maps each distinct call site to the number of times it is executed. The last is the *global variable* profile, which maps each global variable to the number of times it is directly referenced.

If we don't have basic block counts from *pixie*, we can try to estimate them. We first divide the program into basic blocks, and connect them into procedures and flow graphs based on the branch structure.* We then identify the loops by computing the dominator relation and finding the back edges, edges each of whose tail dominates its head. A loop consists of the set of back edges leading to a single dominator, together with the edges that appear on any path from the dominator to the head of one of the back edges [1]. We also build a static call graph by finding all the direct calls in the

* The Mips code generation is stylized enough that we can recognize indirect jumps that represent case-statements, and can deduce what the possible successor blocks are.

program; this graph will not include calls through procedure variables.

Given this information, we considered four different ways of estimating basic blocks counts. The first is the *loop-only* estimate, in which a block’s count is initially 1 and is multiplied by 3 for each loop that contains it; this ignores the effects of the call graph. The second is the *leaf-loop* estimate, in which the loop-only count is multiplied by 1024 if the block is contained in a leaf procedure, 512 if it is no more than one from a leaf procedure, and so on with powers of 2 up to 1. The third is the *call-loop* estimate, in which the loop-only count is multiplied by the static number of direct calls of the block’s procedure. The fourth is the *call+1-loop* estimate, which is the loop-only count is multiplied by one more than the static number of direct calls of the block’s procedure. The call+1-loop estimate is like the call-loop estimate, except that procedures that are called only indirectly will not be shut out altogether; unfortunately procedures that are never called are similarly readmitted.

An optimizer would use a profile by selecting the most frequent entries in it and doing something special to them: promoting them to registers, optimizing them extra hard, or whatever. The question is how well a candidate profile, real or estimated, predicts the behavior described by a reference profile. For this study we considered two abstract methods of evaluating a candidate profile.

The first method, *specific matching*, is to take the top n entries of the candidate profile and see how many of them are also in the top n entries of the reference profile. For instance, consider the procedure profiles in Figure 1. If we let $n = 8$, we see that the first 8 members of the candidate profile include 5 of the first 8 members of the reference profile. Thus the candidate profile gets a score of $5/8$, or 0.625.

306068	full_row	878373	cdist0
242254	force_lower	245657	d1_order
190252	malloc	138058	force_lower
190250	free	72374	setp_disjoint
126993	set_or	48672	cdist01
86450	setp_implies	47029	malloc
71835	d1_order	47027	free
60790	set_clear	36491	full_row
• • •		• • •	
		19131	set_or
		15065	set_clear
		• • •	
		4792	setp_implies
		• • •	

Figure 1. Candidate profile (left) and reference profile.

The second method, *frequency matching*, is to take the top n entries of the candidate profile and look up their frequencies in the reference profile, and then compare the total to the total of the top n entries of the reference profile. For example, taking the profile in Figure 1 and again assuming $n = 8$, the total of the candidate’s top 8 entries

as revealed by the reference profile is 553250, while the total of the reference profile's top 8 entries is 1513681. By this measure, then, the candidate profile gets a score of $553250/1513681$, or 0.365. Note that specific matching is symmetric (we get the same score comparing A to B as comparing B to A), but frequency matching is asymmetric.

Applying this approach to all four kinds of profiles, for different values of n , should give us some notion of how well one profile might predict another. To apply this understanding more specifically, we also did some rough computations of the stability of the profiles when applied in two specific ways. One application is the promotion of global variables to registers. The other is intensive optimization of the most frequently called procedures.

We should note one important limitation of this approach. It does not address the stability of a profile over successive versions of the same program undergoing development. One would expect that some kinds of profiles, such as global variable use or procedure invocation, might be relatively stable even when the program is modified. One might argue that a program under development will not be run enough times to merit profile-based optimization, but it would still be interesting to know whether it would be feasible. A thorough study of this question may be in order, but is not considered here.

3. Programs and data used

Our test suite consists of eleven programs. Two of them, a text editor and a drawing editor, are interactive. Two are CAD tools used at WRL. Two are different C compiler front ends; one is recursive descent, the other yacc-based. Three of them are SPEC benchmarks. Figure 2 describes the complete test suite.

<i>program</i>	<i>description</i>
bisim	multi-level machine simulator
bitv	timing verifier
udraw	drawing editor
egrep	file searcher
sed	stream editor
Gosling emacs	text editor
yacc	parser generator
ccom	Titan C front end
gcc1	gnu C front end
eqtott	truth table generator
espresso	set operation benchmark

Figure 2. The eleven test programs.

Wherever possible, we gave the programs quite different input data, in the hopes of maximizing the differences in their behavior. We ran bisim three different ways: completely high-level simulation, high-level functional units with a transistor-level register file, and transistor-level functional units with a high-level register file. Bitv was run to verify a datapath, a register file, and a write buffer. The drawing editor was used to draw schematics and also a home landscape design. Egrep and sed were run

with both simple and complicated patterns, and with large and small inputs. Emacs was used to edit source files, English text files, and very long simulation configuration files. Yacc was used with a high-level language grammar, an intermediate language grammar, and a command grammar for a window manager. The two C compilers were both run with two source files written by humans and two source files generated by the C++ front end. The eqntott and espresso benchmarks from SPEC were run with inputs provided by SPEC.

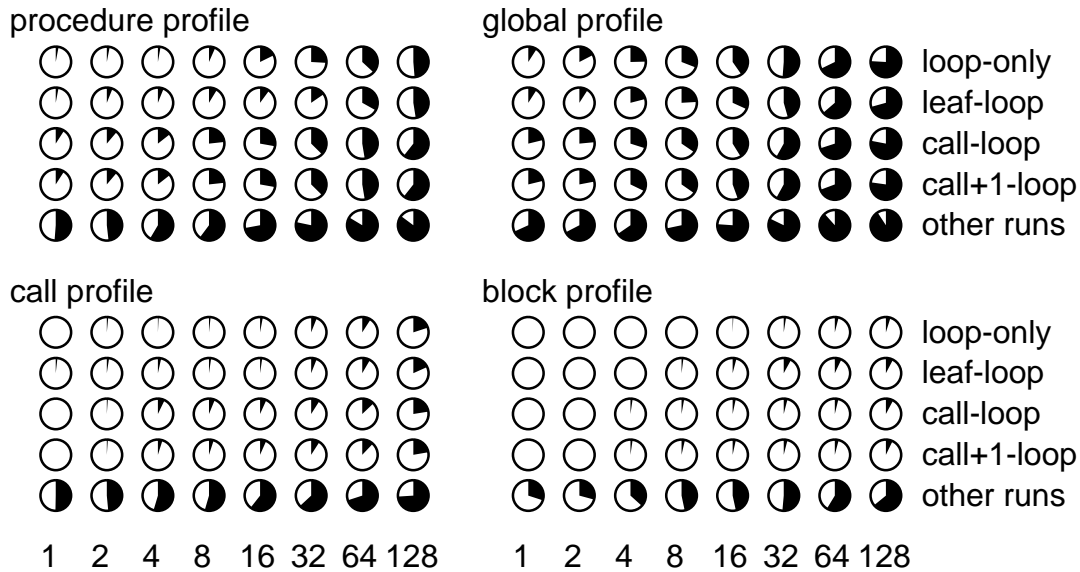


Figure 3. Average specific matching score.

4. Results

4.1. Specific matching

Our first result assumes that we score candidate profiles by the specific matching criterion, for $n = 1, 2, 4, 8, 16, 32, 64,$ and 128 . Given a test program and a value of n , we proceeded as follows. An estimated profile was scored against each real profile for the same test program; we then averaged these scores. Each real profile was scored against each of the *other* real profiles, but not against itself; we then averaged all the scores comparing two real profiles. For each test program and each value of n , this gave us 20 scores: the cross product of four profile classes and five estimate classes (more precisely, four estimate classes and also real profiles from other runs). We then averaged these scores over all programs; this double averaging gave each program equal weight even though some had more datasets than others.

The results are shown in Figure 3. The fraction of the circle filled with black is the score, so a completely black circle is perfect and a completely white circle is terrible. We can see that predicting which globals will be used is fairly easy, probably because there are fewer of them than there are of the other profiled entities. The call-loop estimates do rather better than the other estimates. As we would expect, actual

profiles do considerably better than estimates, but even actual profiles do disappointingly badly at predicting which basic blocks will be executed most.

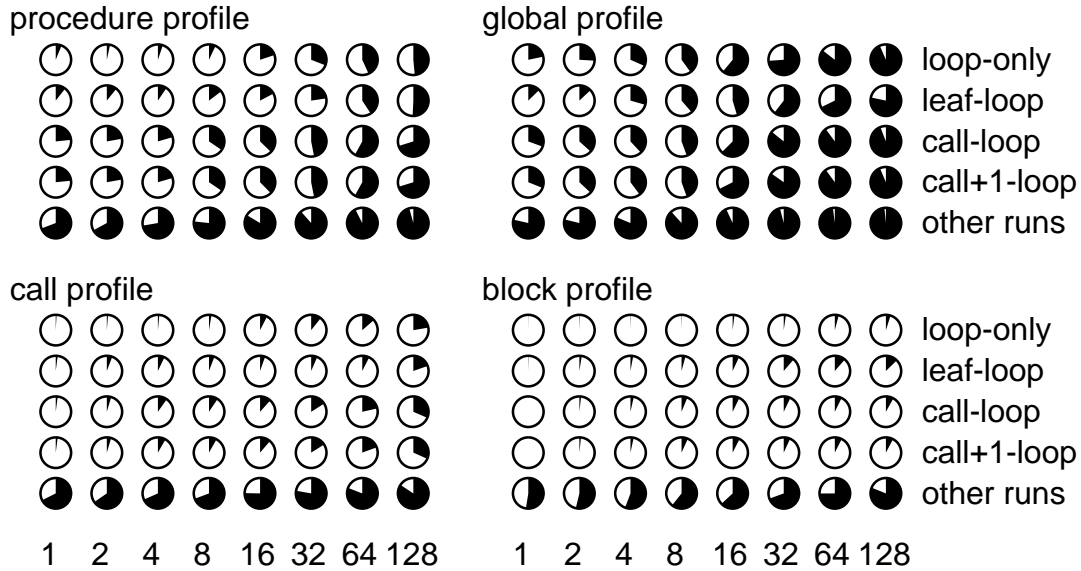


Figure 4. Average frequency matching score.

4.2. Frequency matching

Our next result has the same structure as the previous result, but it assumes frequency matching instead of specific matching. Again, we used $n = 1, 2, 4, 8, 16, 32, 64, \text{ and } 128$. Each profile’s scores were again averaged over all the profiles it was compared against, and the resulting averages were again averaged over the eleven test programs.

The results are shown in Figure 4. We were rather more successful at frequency matching than at specific matching.* The trends, however, are much the same: globals are easy to predict, blocks are hard, call-loop estimates work better than the others, and actual profiles work best of all.

4.3. Differences between test programs

There is a substantial variation in the predictability of the different programs. Figure 5 shows the average score for real (not estimated) profiles, using the frequency matching criterion. This is the fifth and tenth rows of Figure 4, broken down by program. Emacs is astonishingly predictable, perhaps because it is built around a Lisp interpreter, so that much of its control logic (and thus much of its variability) is hidden in the data structure. This argument would lead us to suppose that gcc1, with a table-driven parser, might be more predictable than ccom, with a recursive descent parser.

* This is not guaranteed in general: the candidate profile in Figure 1, for example, got a better score at specific matching.

But in fact ccom is noticeably more predictable than gcc1. The least predictable programs are sed and eqntott, which is a little surprising because they are among the smallest.

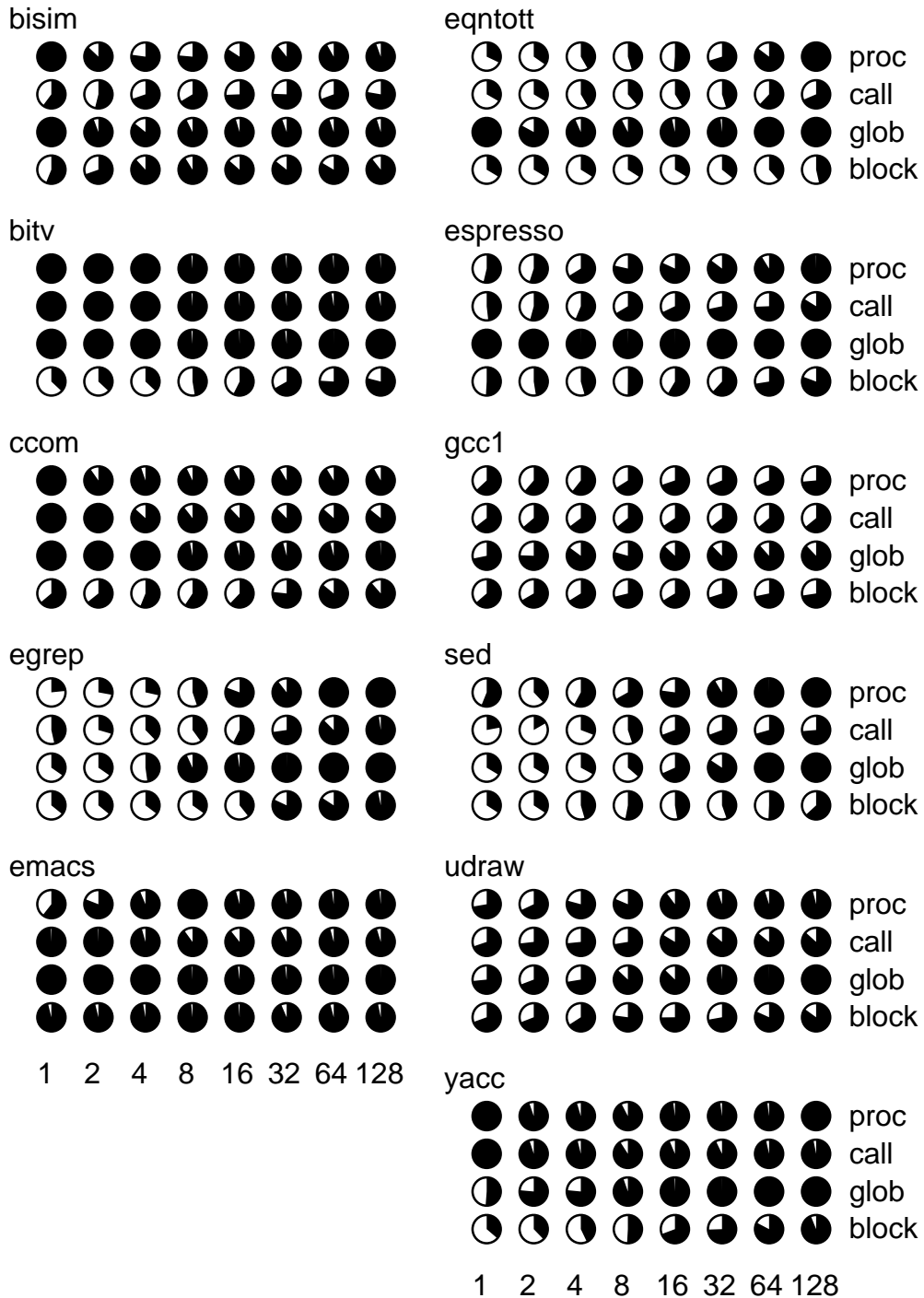


Figure 5. Average frequency matching scores for real profiles.

4.4. Global register allocation

To apply this technique to a realistic specific example, let us suppose that we suddenly have eight registers available that we can use to promote eight global variables or constants. The payoff of doing this is that all the loads and stores of the globals we select will be removed. We can estimate our improvement in performance by counting the executions of these loads and stores and dividing the total by the total number of instructions executed.* We did this both for a reference profile (to see how well we could possibly have done) and for a candidate profile, in each case computing the counts using the reference profile.






	improv	max	ratio
loop-only	1.3%	2.7%	
leaf-loop	1.1%	2.7%	
call-loop	1.2%	2.7%	
call+1-loop	1.3%	2.7%	
other runs	2.3%	2.7%	

Figure 6. Improvement from global register allocation.

The results are shown in Figure 6. This optimization by itself doesn't do a lot for performance: even if magically driven by the counts from the reference profile, the improvement in performance is only 2.7%. A good estimated profile gives us about half of the maximum possible performance improvement, and an actual profile gives us about 85% of the maximum.

4.5. Selective intensive optimization

As a second specific example, let us suppose we have an excellent but expensive optimization algorithm that will cut the execution time of any procedure in half, but that is so expensive that we can apply it only to 5% of our procedures. We will select as the procedures to optimize those we believe will be invoked most often, by picking the first 5% of the entries in the procedure invocation profile. As before, we will do this both for a candidate profile and also for a reference profile; we will compute the improvement in performance using only the counts from the reference profile.

The results are shown in Figure 7. This optimization would speed up our programs by a third if it were driven by a perfect profile. A real profile gives us about three-fourths of that, but even the best estimated profile -- which oddly enough was the simple loop-only estimate -- gives us barely one-fourth.

* This does not take pipeline stalls into account, nor does it consider cache effects, which are likely to increase the benefit of promoting globals to registers. It also assumes that the globals selected are not ineligible because of aliasing. We are interested only in rough numbers here, as an example.

	improv	max	ratio
loop-only	7.4%	31.2%	
leaf-loop	3.7%	31.2%	
call-loop	7.3%	31.2%	
call+1-loop	7.3%	31.2%	
other runs	24.2%	31.2%	

Figure 7. Improvement from selective intensive optimization.

5. Conclusions

Real profiles from different runs worked much better than the estimated profiles discussed in this paper. The best estimations were usually those that combined loop nesting level with static call counts. Basing the estimate on the procedure's distance from leaves of the call graph was less effective. There may of course still be better ways to estimate a profile: this is an interesting open question both in the general case and in specific applications.

Even a real profile was never as good as a perfect profile from the same run being measured. It was often quite close, however, and was usually at least half as good. Profile-based optimization would seem to have a future, but we must be careful how we measure it, lest we expect more than it can really deliver.

Acknowledgements

My thanks to Alan Eustace for goading me into finally doing this study, and to Patrick Boyle, Mary Jo Doherty, Ramsey Haddad, and Joel McCormack for helping me obtain some of the data.

References

- [1] Alfred V. Aho, Ravi Sethi, and Jeffrey D. Ullman. *Compilers: Principles, Techniques, and Tools*, pp. 602-605. Addison-Wesley, 1986.
- [2] Joseph A. Fisher, John R. Ellis, John C. Rutenber, and Alexandru Nicolau. Parallel processing: A smart compiler and a dumb machine. *Proceedings of the SIGPLAN '84 Symposium on Compiler Construction*, pp. 37-47. Published as *SIGPLAN Notices 19* (6), June 1984.
- [3] Scott McFarling. Program optimization for instruction caches. *Third International Symposium on Architectural Support for Programming Languages and Operating Systems*, pp. 183-191, April 1989. Published as *Computer Architecture News 17* (2), *Operating Systems Review 23* (special issue), *SIGPLAN Notices 24* (special issue).
- [4] MIPS Computer Systems, Inc. *Language Programmer's Guide*, 1986.

- [5] Scott McFarling and John Hennessy. Reducing the cost of branches. *Proceedings of the 13th Annual Symposium on Computer Architecture*, pp. 396-403. Published as *Computer Architecture News 14* (2), June 1986.
- [6] Karl Pettis and Robert C Hansen. Profile guided code positioning. *Proceedings of the SIGPLAN '90 Conference on Programming Language Design and Implementation*, pp. 16-27. Published as *SIGPLAN Notices 25* (6), June 1990.
- [7] Vatsa Santhanam and Daryl Odnert. Register allocation across procedure and module boundaries. *Proceedings of the SIGPLAN '90 Conference on Programming Language Design and Implementation*, pp. 28-39. Published as *SIGPLAN Notices 25* (6), June 1990.
- [8] David W. Wall. Global register allocation at link-time. *Proceedings of the SIGPLAN '86 Symposium on Compiler Construction*, pp. 264-275. Published as *SIGPLAN Notices 21* (7), July 1986. Also available as WRL Research Report 86/3.

WRL Research Reports

“Titan System Manual.”

Michael J. K. Nielsen.

WRL Research Report 86/1, September 1986.

“Global Register Allocation at Link Time.”

David W. Wall.

WRL Research Report 86/3, October 1986.

“Optimal Finned Heat Sinks.”

William R. Hamburguen.

WRL Research Report 86/4, October 1986.

“The Mahler Experience: Using an Intermediate Language as the Machine Description.”

David W. Wall and Michael L. Powell.

WRL Research Report 87/1, August 1987.

“The Packet Filter: An Efficient Mechanism for User-level Network Code.”

Jeffrey C. Mogul, Richard F. Rashid, Michael J. Accetta.

WRL Research Report 87/2, November 1987.

“Fragmentation Considered Harmful.”

Christopher A. Kent, Jeffrey C. Mogul.

WRL Research Report 87/3, December 1987.

“Cache Coherence in Distributed Systems.”

Christopher A. Kent.

WRL Research Report 87/4, December 1987.

“Register Windows vs. Register Allocation.”

David W. Wall.

WRL Research Report 87/5, December 1987.

“Editing Graphical Objects Using Procedural Representations.”

Paul J. Asente.

WRL Research Report 87/6, November 1987.

“The USENET Cookbook: an Experiment in Electronic Publication.”

Brian K. Reid.

WRL Research Report 87/7, December 1987.

“MultiTitan: Four Architecture Papers.”

Norman P. Jouppi, Jeremy Dion, David Boggs, Michael J. K. Nielsen.

WRL Research Report 87/8, April 1988.

“Fast Printed Circuit Board Routing.”

Jeremy Dion.

WRL Research Report 88/1, March 1988.

“Compacting Garbage Collection with Ambiguous Roots.”

Joel F. Bartlett.

WRL Research Report 88/2, February 1988.

“The Experimental Literature of The Internet: An Annotated Bibliography.”

Jeffrey C. Mogul.

WRL Research Report 88/3, August 1988.

“Measured Capacity of an Ethernet: Myths and Reality.”

David R. Boggs, Jeffrey C. Mogul, Christopher A. Kent.

WRL Research Report 88/4, September 1988.

“Visa Protocols for Controlling Inter-Organizational Datagram Flow: Extended Description.”

Deborah Estrin, Jeffrey C. Mogul, Gene Tsudik, Kamaljit Anand.

WRL Research Report 88/5, December 1988.

“SCHEME->C A Portable Scheme-to-C Compiler.”

Joel F. Bartlett.

WRL Research Report 89/1, January 1989.

“Optimal Group Distribution in Carry-Skip Adders.”

Silvio Turrini.

WRL Research Report 89/2, February 1989.

“Precise Robotic Paste Dot Dispensing.”

William R. Hamburguen.

WRL Research Report 89/3, February 1989.

“Simple and Flexible Datagram Access Controls for Unix-based Gateways.”

Jeffrey C. Mogul.

WRL Research Report 89/4, March 1989.

“Spritely NFS: Implementation and Performance of Cache-Consistency Protocols.”

V. Srinivasan and Jeffrey C. Mogul.

WRL Research Report 89/5, May 1989.

“Available Instruction-Level Parallelism for Superscalar and Superpipelined Machines.”

Norman P. Jouppi and David W. Wall.

WRL Research Report 89/7, July 1989.

“A Unified Vector/Scalar Floating-Point Architecture.”

Norman P. Jouppi, Jonathan Bertoni, and David W. Wall.

WRL Research Report 89/8, July 1989.

“Architectural and Organizational Tradeoffs in the Design of the MultiTitan CPU.”

Norman P. Jouppi.

WRL Research Report 89/9, July 1989.

“Integration and Packaging Plateaus of Processor Performance.”

Norman P. Jouppi.

WRL Research Report 89/10, July 1989.

“A 20-MIPS Sustained 32-bit CMOS Microprocessor with High Ratio of Sustained to Peak Performance.”

Norman P. Jouppi and Jeffrey Y. F. Tang.

WRL Research Report 89/11, July 1989.

“The Distribution of Instruction-Level and Machine Parallelism and Its Effect on Performance.”

Norman P. Jouppi.

WRL Research Report 89/13, July 1989.

“Long Address Traces from RISC Machines: Generation and Analysis.”

Anita Borg, R.E.Kessler, Georgia Lazana, and David W. Wall.

WRL Research Report 89/14, September 1989.

“Link-Time Code Modification.”

David W. Wall.

WRL Research Report 89/17, September 1989.

“Noise Issues in the ECL Circuit Family.”

Jeffrey Y.F. Tang and J. Leon Yang.

WRL Research Report 90/1, January 1990.

“Efficient Generation of Test Patterns Using Boolean Satisfiability.”

Tracy Larrabee.

WRL Research Report 90/2, February 1990.

“Two Papers on Test Pattern Generation.”

Tracy Larrabee.

WRL Research Report 90/3, March 1990.

“Virtual Memory vs. The File System.”

Michael N. Nelson.

WRL Research Report 90/4, March 1990.

“Efficient Use of Workstations for Passive Monitoring of Local Area Networks.”

Jeffrey C. Mogul.

WRL Research Report 90/5, July 1990.

“A One-Dimensional Thermal Model for the VAX 9000 Multi Chip Units.”

John S. Fitch.

WRL Research Report 90/6, July 1990.

“1990 DECWRL/Livermore Magic Release.”

Robert N. Mayo, Michael H. Arnold, Walter S. Scott, Don Stark, Gordon T. Hamachi.

WRL Research Report 90/7, September 1990.

“Pool Boiling Enhancement Techniques for Water at Low Pressure.”

Wade R. McGillis, John S. Fitch, William R. Hambrun, Van P. Carey.

WRL Research Report 90/9, December 1990.

WRL Technical Notes

“TCP/IP PrintServer: Print Server Protocol.”

Brian K. Reid and Christopher A. Kent.

WRL Technical Note TN-4, September 1988.

“TCP/IP PrintServer: Server Architecture and Implementation.”

Christopher A. Kent.

WRL Technical Note TN-7, November 1988.

“Smart Code, Stupid Memory: A Fast X Server for a Dumb Color Frame Buffer.”

Joel McCormack.

WRL Technical Note TN-9, September 1989.

“Why Aren’t Operating Systems Getting Faster As Fast As Hardware?”

John Ousterhout.

WRL Technical Note TN-11, October 1989.

“Mostly-Copying Garbage Collection Picks Up Generations and C++.”

Joel F. Bartlett.

WRL Technical Note TN-12, October 1989.

“Limits of Instruction-Level Parallelism.”

David W. Wall.

WRL Technical Note TN-15, December 1990.

“The Effect of Context Switches on Cache Performance.”

Jeffrey C. Mogul and Anita Borg.

WRL Technical Note TN-16, December 1990.

“MTOOL: A Method For Detecting Memory Bottlenecks.”

Aaron Goldberg and John Hennessy.

WRL Technical Note TN-17, December 1990.

“Predicting Program Behavior Using Real or Estimated Profiles.”

David W. Wall.

WRL Technical Note TN-18, December 1990.