DiffTrace: Efficient Whole-Program Trace Analysis and Diffing

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ABSTRACT

Abstract to be written

KEYWORDS

diffing, tracing, debugging

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1 INTRODUCTION

When the next version of an HPC software system is created, logical errors often get introduced. To maintain productivity, designers need effective and efficient methods to locate these errors. Given the increasing use of hybrid (MPI + X) codes and library functions, errors may be introduced through a usage contract violation at any one of these interfaces. Therefore, tools that record activities at multiple APIs are necessary. Designs find most of these bugs manually, and the efficacy of a debugging tool is often measured by how well it can highlight the salient differences between the executions of two versions of software. Given the huge number of things that could be different – individual iterative patterns of function calls, groups of functions calls, or even specific instruction types (e.g., non-vectorized versus vectorized floating-point dot vector loops) – designers cannot often afford to rerun the application multiple times to collect each facet of behavior separately. These issues are well summarized in many recent studies [20]

One of the major challenges of HPC debugging is the huge diversity of the applications, which encompass domains such as computational chemistry, molecular dynamics, and climate simulation. In addition, there are many types of possible âĂIJbugsâĂİ or, more precisely, errors. An **error** may be a deadlock or a resource leak. These errors may be caused by different **faults**: an unexpected message reordering rule (for a deadlock) or a forgotten free statement (for a resource leak). There exists a collection of scenarios in which a bug can be introduced: when developing a brand new application, optimizing an existing application, upscaling an application, porting to a new platform, changing the compiler, or even changing compiler flags. Unlike traditional software, there are hardly any bug-repositories, collection of trace data or debugging-purpose benchmarks in HPC community. The heterogeneous nature of HPC bugs make developers come up with their own solutions to resolve specific class of bugs on specific architecture or platforms that are not usable on other [20].

When a failure occurs (e.g., deadlock or crash) or the application outputs an unexpected result, it is not economic to rerun the application and consume resources to reproduce the failure. In addition, HPC bugs might not be reproducible due to non-deterministic behavior of most of HPC applications. Also the failure might be caused by a bug present at different APIs, system levels or network, thus multiple reruns might be needed to locate the buggy area. In our previous work[43], we have introduced ParLOT that collects whole program function call traces efficiently using dynamic binary instrumentation. ParLOT captures function calls and returns at different levels (e.g., source-code and library) and incrementally compress them on-the-fly, resulting in low runtime overhead and significantly low required bandwidth, preserving the whole-program dynamic behavior for offline analysis.

In the current work, we introduce DiffTrace, a tool-chain that post-mortem analyze ParLOT traces in order to supply developers with information about dynamic behavior of HPC applications at different levels towards debugging. Topology of HPC tasks on both distributed and shared memory often follow a "symmetric" control flow such as SPMD, master/worker and odd/even where multiple tasks contain *similar* events in their control flow. HPC bugs often manifest themselves as divergence in the control flow of processes comparing to what was expected. In other words, HPC bugs violates the rule of "symmetric" and "similar" control flow of one or more thread/process in typical HPC applications based on the original topology of the application. We believe that finding the dissimilarities among traces is the essential initial step towards finding the bug manifestation, and consequently the bug root cause. Large-scale HPC application execution would result in thousands of ParLOT trace files due to execution of thousands of processes and threads. Since HPC applications spend most of their time in an outer

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main loop, every single trace file also may contain million-long sequence of trace entries (i.e., function calls and returns). Finding the bug manifestation (i.e., dissimilarities caused by the bug) among large number of long traces is the problem of finding the needle in the haystack.

Decompressing ParLOT traces collected from long-running large-scale HPC applications for offline analysis produce overwhelming amount of data. However, missing any piece of collected data may result in loosing key information about the application behavior. We propose a variation of NLR (Nested Loop Recognition) algorithm [25] that takes a sequence of trace entries as input and by recursively detecting repetitive patterns, re-compresses traces into "iterative sets" in a lossless fashion (intra-trace compression). Analyzing the application execution as a whole is another goal that we are pursuing in this work. By extracting *attributes* from pre-processed traces, we inject them a concept hierarchy data structure called Concept Lattice [16]. Concept lattices give us the capability of reducing the search space from thousands of instances to just a few *equivalent behavior classes of traces* by measuring the similarity of traces[3]

** TODO: Highlights of results obtained as a result of the above thinking should be here. THis typically comes before ROADMAP of paper.

In summary, here are our main contributions:

- we have a powerful combination of ideas to locate bugs
- A variation of NLR algorithm to compress traces in lossless fashion for easier analysis and detecting (broken) loop structures
- FCA-based clustering of similar behavior traces, efficient,
- Ranking system based on delta-sim
- Visualization diffNLR

The rest of the paper is as follows:
- Sec 2 talks about backgrounds
- Sec 3: Talks about the design of diffTrace
- Sec 4: Evaluates diffNLR by initial recommendation turns into NLR-observable bug and confusion matrix scores how many TP,FP,TN,FN
- Sec 5 major related work will have a detailed discussion of related work
- Sec 6 discusses the potential limitations, future work, and conclusion.

2 BACKGROUND AND RELATED WORK

Why we need our components:

- ParLOT collects whole program function call trace with the mindset of paying a little upfront and save resource and time cost of reproducing the bug.

- detection of loops, lossless Compression, easier to analyze, information about loop structures, how many iteration each loop executed matters, broken loop matters

- Concept lattices, throw inter-process information, similarity, clustering

- diffNLR visualizes pairs of traces and reflect their differences where they are supposed to be equal.

2.1 Parlot Summary (changeme)

- why binary instrumentation? no need to modify the code to instrument - no need to recompile

- Parlot is portable, scalable, efficient,

mini related work discussion here, mainly to refocus mind to accepting that binary tracing has several advantages that don't come with other tracing approaches such as Dyninst etc.

2.2 Equivalencing behavior via concept lattices (changeme)

this is how it is cleanly defined (use our context or examples)

e.g. high-level : objects to attributes

in our case objects can be... and attributes can be

how we use them is ...

- Vijay Garg - Applications of lattice theory in distributed systems
- Dimitry Ignatov [?] - Concept Lattice Applications in Information Retrieval
- [16] [19] [4] [18]
  Similarity measurement using FCA [3]

2.2.1 *Attribute creation...* There are many of them (others have not

2.2.2 *incremental algos.* challenges : need incremental algo...

end

2.3 Loop structure detection

loop detection has been addressed in xyz

challenges in our context are xyz...

highlights of what you did (briefly) and why it can help

2.4 diffing (changeme)

what you adapted

how does it help

[36]

2.5 STAT

Parallel debugger STAT[1]

- STAT gathers stack traces from all processes
- Merge them into prefix tree
- Groups processes that exhibit similar behavior into equivalent classes
- A single representative of each equivalence can then be examined with a full-featured debugger like TotalView or DDT

What STAT does not have?

- FP debugging
- Portability (too many dependencies)
- Domain-specific
- Loop structures and detection

2.6 Program Understanding

- Score-P [26]
- TAU [41]
- ScalaTrace: Scalable compression and replay of communication traces for HPC [38]
- Barrier Matching for Programs with Textually unaligned barriers [46]
- Pivot Tracing: Dynamic causal monitoring for distributed systems - Johnathan mace [32]
- Automated Charecterization of parallel application communication patterns [40]
- Problem Diagnosis in Large Scale Computing environments [34]
- Probablistic diagnosis of performance faults in large-scale parallel applications [28]
- detecting patterns in MPI communication traces - robert preissl [39]
- D4: Fast concurrency debugging with parallel differntial analysis - bozhen liu [31]
- Marmot: An MPI analysis and checking tool - bettina krammer [27]
- MPI-checker - Static Analysis for MPI - Alexandrer droste [15]
- STAT: stack trace analysis for large scale debugging - Dorian Arnold [1]
- DMTracker: Finding bugs in large-scale parallel programs by detecting anomaly in data movements [17]
- SyncChecker: Detecting synchronization errors between MPI applications and libraries - [11]
- Model Based fault localization in large-scale computing systems - Naoya Maruyama [33]
- Synoptic: Studying logged behavior with inferred models - ivan beschastnikh [5]
- Mining temporal invariants from partially ordered logs - ivan beschastnikh [7]
- Scalable Temporal Order Analysis for Large Scale Debugging - Dong Ahn [2]
- Inferring and asserting distributed system invariants - ivan beschastnikh - stewart grant [21]
- PRODOMETER: Accurate application progress analysis for large-scale parallel debugging - subatra mitra [35]
- Automaded : Automata-based debugging for dissimilar parallel tasks - greg [9]
- Automaded : large scale debugging of parallel tasks with Automaded - ignacio [29]
- Inferring models of concurrent systems from logs of their behavior with CSight - ivan [6]

2.7 Trace Analysis

- Trace File Comparison with a hierarchical Sequence Alignment algorithm [44]
- structural clustering : matthias weber [45]
- building a better backtrace: techniques for postmortem program analysis - ben liblit [30]
- automatically charecterizing large scale program behavior - timothy sherwood [42]

2.8 Visualizations

- Combing the communication hairball: Visualizing large-scale parallel execution traces using logical time - katherine e isaacs [23]
- recovering logical structure from charm++ event traces [22]
- ShiViz - Debugging distributed systems - [8]

2.9 Concept Lattice and LCA

- Vijay Garg - Applications of lattice theory in distributed systems
- Dimitry Ignatov [?] - Concept Lattice Applications in Information Retrieval
- [16] [19] [4] [18] [36]

2.10 Repetitive Patterns

- [12] [24] [37] [14] [13]

3 DFFTRACE TOOL ARCHITECTURE

3.1 General Idea

Here is a general overview of DiffTrace and its components

- Motivating example
- Problem statement
- Potential Approaches and Related Work
- Next subsections will explain the components that we have in our framework and the corresponding related work and background

3.2 Fault Injection

3.3 ParLOT

2-3 paragraph explanation about ParLOT and its mechanism [43]

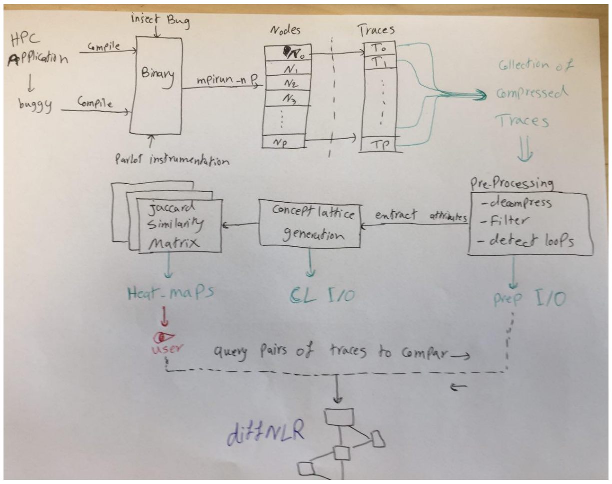
3.4 Filter

Include a table with all filters and their regular expressions

3.4.1 *General Filters.*

- Returns
- .plt
- Memory
- Network

Figure 1: diffTrace Overview



- Polling
- String
- Customize
- IncludeEverything

3.4.2 Target Filters.

- MPI_
- MPIall
- MPI_ Collectives
- MPI_ Send/Recv
- OMPall
- OMPcritical
- OMPmutex

3.5 Nested Loop Recognition

3.5.1 Background.

3.5.2 Implementation.

3.6 Concept Lattice Analysis

3.6.1 Background.

- FCA (formal concept analysis) background and citations
- FCA applications in all areas
- FCA applications in Data Mining and Information Retrieval
- FCA applications in distributed systems (Garg's work)
- intro to Concept, Object, Attribute and other definitions

3.6.2 Objects/Attributes. Mapping of Object/Attribute (general) to Trace/Attribute (clTrace)

What do we expect to gain by doing so

- Single entity represents the whole execution of HPC application (can be used as signature/model in ML)
- Classifying similar behavior objects(traces)
- Efficient Incremental CL building makes it scalable
- Efficient full pair-wise Jaccard Similarity Matrix extraction

3.6.3 CL generation.

- background
- current approach

3.6.4 Jaccard Similarity Matrix.

- background
- LCA
- Benefits

3.7 diffNLR

- motivation
- diff algorithm
- visualization

3.8 FP-Trace

4 EXPERIMENTAL STUDIES

Filter	Attributes	Top Process diffNLR Candidates	Top Thread diffNLR Candidates
11.mpi.cust.0K10	sing.log10	1:(25)r259.10699.0,(65)r265.20114.0 2:(20)r259.10698.0,(75)r265.20116.0 3:(0)r259.10694.0,(55)r265.20112.0	1:(2)r259.10694.2,(78)r265.20116.3 2:(17)r259.10697.2,(64)r265.20113.4 3:(49)r265.20110.4,(58)r265.20112.3
11.mpi.cust.0K10	doub.orig	1:(25)r259.10699.0,(65)r265.20114.0 2:(20)r259.10698.0,(75)r265.20116.0 3:(0)r259.10694.0,(55)r265.20112.0	1:(32)r259.10700.2,(54)r265.20111.4 2:(14)r259.10696.4,(74)r265.20115.4 3:(53)r265.20111.3,(53)r265.20111.3
11.mpicol.cust.0K10	doub.orig	1:(25)r259.10699.0,(65)r265.20114.0 2:(20)r259.10698.0,(75)r265.20116.0 3:(0)r259.10694.0,(55)r265.20112.0	1:(32)r259.10700.2,(54)r265.20111.4 2:(14)r259.10696.4,(74)r265.20115.4 3:(53)r265.20111.3,(53)r265.20111.3
01.mpicol.0K10	doub.orig	1:(25)r259.10699.0,(65)r265.20114.0 2:(20)r259.10698.0,(75)r265.20116.0 3:(0)r259.10694.0,(55)r265.20112.0	1:(32)r259.10700.2,(54)r265.20111.4 2:(14)r259.10696.4,(74)r265.20115.4 3:(53)r265.20111.3,(53)r265.20111.3
11.mpicol.cust.0K10	sing.orig	1:(25)r259.10699.0,(65)r265.20114.0 2:(20)r259.10698.0,(75)r265.20116.0 3:(0)r259.10694.0,(55)r265.20112.0	1:(2)r259.10694.2,(78)r265.20116.3 2:(17)r259.10697.2,(64)r265.20113.4 3:(49)r265.20110.4,(58)r265.20112.3
01.mpicol.0K10	doub.actual	1:(25)r259.10699.0,(65)r265.20114.0 2:(20)r259.10698.0,(75)r265.20116.0 3:(0)r259.10694.0,(55)r265.20112.0	1:(32)r259.10700.2,(54)r265.20111.4 2:(14)r259.10696.4,(74)r265.20115.4 3:(53)r265.20111.3,(53)r265.20111.3

Figure 2: Recommendation Table Sample for one of the bugs

5 RESULTS

Table 1 describes the bug that I injected to ILCS-TSP

5.1 MPI Bugs

6 CASE STUDIES

6.0.1 Case Study: ILCS. ILCS [10]

6.0.2 Case Study: MFEM.

7 DISCUSSION AND FUTURE WORK

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Table 1: Injected Bugs to ILCS-TSP

ID	Level	Bugs	Description
1	MPI	allRed1wrgOp-1-all-x	Different operation (MPI_MAX) in only one (buggyProc) for first MPI_ALLREDUCE() – L229:ilcsTSP.c
2		allRed1wrgSize-1-all-x	Wrong size in only one (buggyProc) for first MPI_ALLREDUCE() – L229:ilcsTSP.c
3		allRed1wrgSize-all-all-x	Wrong Size in all processes for first MPI_ALLREDUCE() – L229:ilcsTSP.c
4		allRed2wrgOp-1-all-x	Different operation (MPI_MAX) in only one (buggyProc) for first MPI_ALLREDUCE() – L277:ilcsTSP.c
5		allRed2wrgSize-1-all-x	Wrong size in only one (buggyProc) for first MPI_ALLREDUCE() – L277:ilcsTSP.c
6		allRed2wrgSize-all-all-x	Wrong Size in all processes for second MPI_ALLREDUCE() – L277:ilcsTSP.c
7		bcastWrgSize-1-all-x	Wrong Size in only one (buggyProc) of MPI_Bcast() – L290:ilcsTSP.c
8		bcastWrgSize-all-all-x	Wrong Size n all processes for MPI_Bcast() – L240:ilcsTSP.c
9	OMP	misCrit-1-1-x	Missing Critical Section in buggyProc and buggyThread – L170:ilcsTSP.c
10		misCrit-all-1-x	Missing Critical Section in buggyThread and all prcoesses – L170:ilcsTSP.c
11		misCrit-1-all-x	Missing Critical Section in buggyProc and all threads – L170:ilcsTSP.c
12		misCrit-all-all-x	Missing Critical Section in all procs and threads – L170:ilcsTSP.c
13		misCrit2-1-1-x	Missing Critical Section in buggyProc and buggyThread – L230:ilcsTSP.c
14		misCrit2-all-1-x	Missing Critical Section in buggyThread – L230:ilcsTSP.c
15		misCrit2-1-all-x	Missing Critical Section in buggyProc and all threads – L230:ilcsTSP.c
16		misCrit2-all-all-x	Missing Critical Section in all procs and threads – L230:ilcsTSP.c
17		misCrit3-1-all-x	Missing Critical Section in buggyProc and all threads – L280:ilcsTSP.c
18		misCrit3-all-all-x	Missing Critical Section in all procs and threads – L280:ilcsTSP.c
19	General	infLoop-1-1-1	Injected an infinite loop after CPU_EXEC() in buggyProc,buggyThread & buggyIter L164:ilcsTSP.c

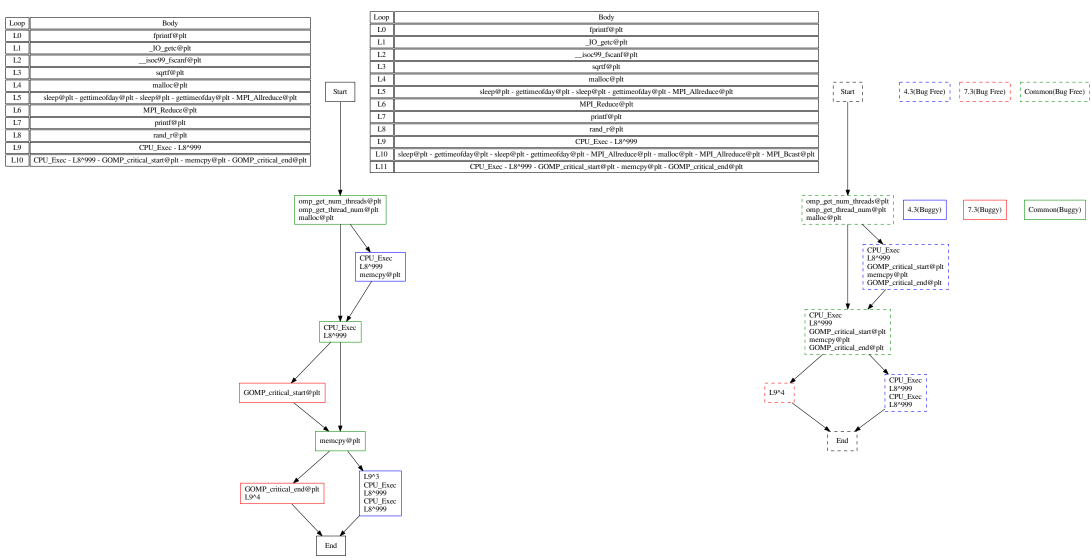

Figure 3: sample diffNLR

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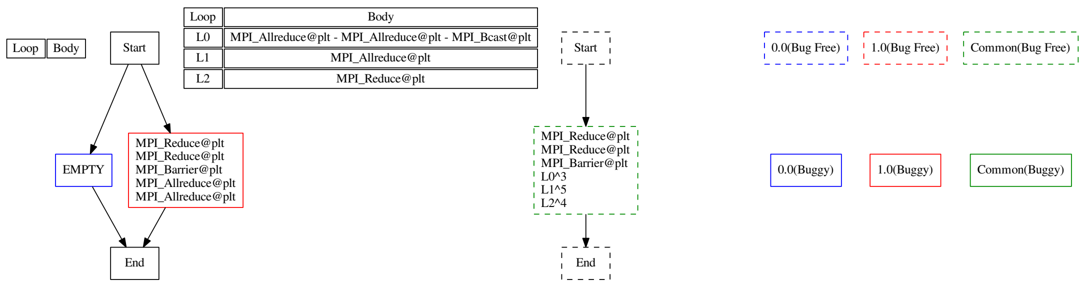

Figure 4: sample diffNLR2

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