Ordering Traces Logically to Identify Lateness in Message-Passing Programs

Katherine E. Isaacs, Todd Gamblin, Abhinav Bhatele, Martin Schulz, Bernd Hamann, and Peer-Timo Bremer

Abstract—Event traces are valuable for understanding the behavior of parallel programs. Automatically analyzing a large parallel trace, however, especially without a specific objective, is difficult. We aid this endeavor by extracting a trace's *logical structure*, an ordering of operations derived from their happened-before relationships while taking into account developer intent. Using this structure, we can calculate an operation's delay relative to its peers on other processes. The logical structure also serves as a platform for comparing and clustering processes as well as highlighting communication patterns in a trace visualization. We present an algorithm for determining this idealized logical structure from traces of message passing programs, and we develop metrics to quantify delays and differences among processes. We implement our techniques in our tool Ravel, a novel parallel trace visualizer that displays both logical and physical timelines. Rather than showing the duration of each operation, we display where delays begin and end, and how they propagate. We apply our approach to traces from several message passing applications, demonstrating the accuracy of our extracted structure and its utility in analyzing these codes.

Index Terms—trace analysis, performance

1 Introduction

Writing an efficient, scalable parallel program that performs well on a range of architectures is challenging. Achieving good performance usually involves several, often tedious, iterations of noticing performance problems, identifying their causes, and reworking the implementation accordingly. One common option to help with this process are tracing tools, which capture communication events and visualize them in timeline views (such as Vampir [1]). However, two factors limit their effective use at scale. First, traces from large numbers of processes or from long-running jobs are prohibitively large. Second, the complex communication patterns common in many large-scale codes are hard to identify and comprehend when plotted with respect to wall-clock time. We need new analysis and visualization tools to help users understand complex parallel execution traces and to aid in determining the information necessary to optimize the analyzed code.

In this paper, we address the difficulties in trace analysis by focusing on the underlying logical communication structure of a message passing program based on the happened-before relationships of traced events across multiple processes. This structure differs from previous analyses in logical time by considering the developers' intended organization when handling concurrent events to establish happened-before relationships at several granularities. Using the information from this logical structure, we define metrics in terms of relationships among logically simultaneous operations across processes, abstracting only the performance critical timing information. Specifically, we define *lateness*, which measures how delayed an operation is relative to its peers, and *differential lateness* which measures how much delay was injected into the system at an operation, allowing analysts to quickly identify delayed processes and the bottlenecks they cause.

One immediate advantage is that since the logical structure aligns communication operations across processes, it leads to cleaner visualizations that more directly expose communication patterns. The logical structure also provides the necessary basis for comparing and clustering processes. Ravel [2], our interactive trace visualization tool, displays traces in both wall-clock and logical time and uses clustering to improve the scalability of the visualization and help users focus on the most important parts of the trace.

We present our algorithm for deriving logical structure and its associated metrics using the LULESH shock hydrodynamics proxy application [3]; a proxy application for the communication in pF3D [4], a laser-plasma interaction code; the SMG2000 semicoarsening multigrid solver benchmark [5]; and the Multi-grid (MG) benchmark from the NAS Parallel Benchmarks (NPB) suite [6], [7] to illustrate our approach.

Further, we demonstrate the effectiveness of our logical structure extraction technique and the utility of our temporal metrics through three case studies. We study multiple implementations of collective operations in MPI [8], an *in situ* merge tree appication [9] for topological data analysis, and a sparse linear solver library [10] via the AMG2013 benchmark [11]. We conduct our studies on an IBM Blue Gene/Q system and on a commodity cluster with Intel Sandy Bridge processors and an Infiniband network.

The major contributions of this work are:

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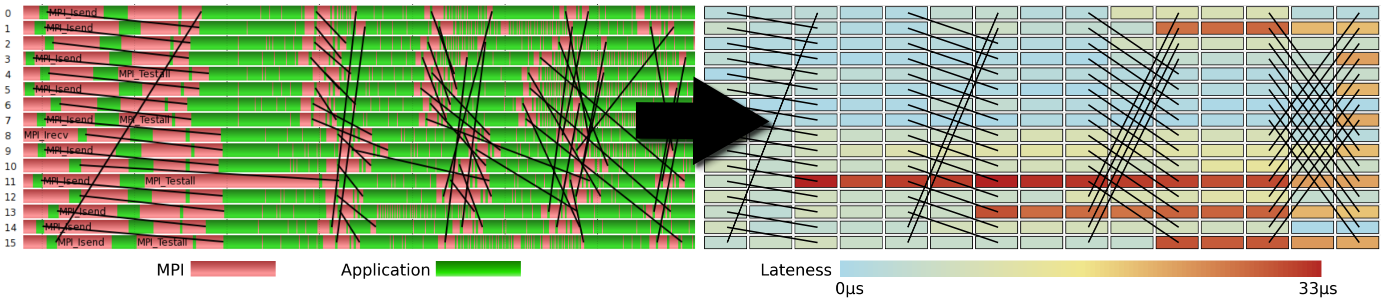


Fig. 1: Trace of a 16 process `MPI_Alltoall` using the dissemination implementation from libNBC [8]. From the raw physical time data, shown on the left using Vampir [1], we deduce a logical structure, visualized on the right, and use this structure to compute a novel lateness metric of each operation, shown on the right using color. In this example, we can clearly see that the lateness from a receive on process 11 propagates to several other processes.

- A set of techniques to extract the logical communication structure of a message passing program from its execution trace;
- Novel metrics, such as lateness, that help identify performance bottlenecks or delays in the execution;
- Case studies demonstrating that the new approach accurately detects and highlights performance characteristics difficult to obtain from existing techniques.

2 Related Work

Parallel execution traces are used for both performance analysis and debugging. Automated trace tools like Kojak [12] or its successor Scalasca [13] can detect given patterns of known performance problems, such as the late arrival of a message, and compute a severity score, which is mapped to source code. While this helps in identifying the locations at which the bottleneck exists, it typically does not make the context or root cause readily available. In particular, while these tools can pinpoint very local performance problems, they cannot identify transitive dependence chains or relations among processes easily. The addition of root cause analysis [14] allows the tracking of delay through dependencies, much like our differential lateness. However, the analysis remains limited to local waiting state calculations instead of taking into account the context of peer operations as done when calculating lateness.

Morajko et al. [15] build per-process causality graphs for discovering structure and detecting propagation and root causes. They aggregate these graphs by identity and compress performance data on the representative graph. This can unduly emphasize boundary behavior of a small number of processes while hiding more extreme behavior of larger clusters.

Another way of analyzing trace data is to determine the critical path through the program and analyze performance in that context [16], [17]. However, it is often unclear how the critical path interacts with the rest of the trace to cause issues. Moreover, critical paths can be lengthy, often require costly reverse playback, and can obscure subpaths of interest.

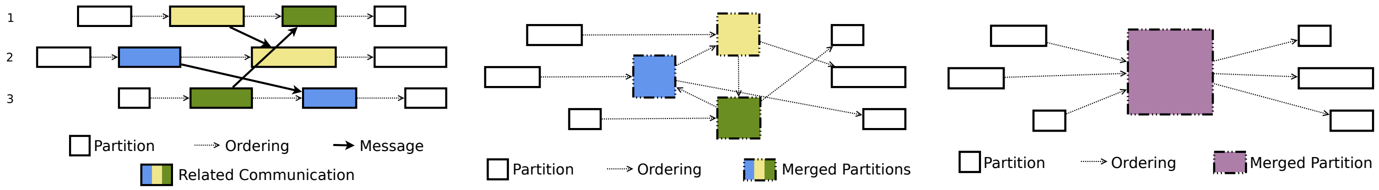
Manual trace analysis is often facilitated through timeline visualization: events are arranged in order of increasing time on the horizontal axis and in rank order by process id on the vertical axis. Fig. 1 (left) is a typical example taken from Vampir [1]. Other trace visualizers like Jumpshot [18] or Paraver [19] provide similar views. While such timelines allow the user to make inferences about timing directly from the spatial layout, excessive detail makes finding areas of interest difficult. It also clutters the visualization and makes interpretation arduous, as dependencies are hard to follow. Logical time trace visualizations have been implemented, mostly for debugging [20], [21], but these incorporate few dependencies and thus place concurrent events as early as possible, and do not incorporate physical time information directly within the view. Our logical structure and metrics provide another way to visualize traces, the details of which can be found in [2]. In this paper, we employ Vampir as one example of an established trace visualization tool using a conventional timeline view and Ravel to illustrate our logical structure and metrics.

Many tools [22], [23], [24] have focused on detecting high-level, statistical program behavior using clustering and wavelet techniques. While these numerical techniques provide useful high-level structure, they do not help programmers understand local logical dependence chains in communication threads. Such algorithms could easily be combined with our approach to display these aggregate metrics within our logical structure.

3 Extracting Logical Structure

In contrast to existing approaches, we transform an event trace into a logical communication structure, and we perform analysis in this context. Throughout, we assume that a parallel trace for a message passing program consists of measured instantaneous events that are either function entry or exit, or communication such as sends, receives, or collectives. We call two matching enter and exit records an operation and two matching send and receive records a message. We further assume, at a minimum, that an execution trace is a series of records of the enter and exit time of each operation that invokes communication, the send and receive time of each point-to-point message, and the processes associated with these operations and messages. In this paper, we focus on MPI, but aside from a few rules for specific MPI operations, our structure algorithm could be applied to any other message-passing model.

The *logical structure* of a program is an ordering of operations consistent with that program, ideally reflecting



(a) Matching sends and receives indicate operations are related and should be merged.

(b) Ordering relations for merged partitions are derived from the pre-merge neighbors.

(c) Strongly connected components are merged into single partitions.

Fig. 2: Mandatory Partitions

the developers' *intended* organization. Due to either programming errors or ambiguities in assigning logical time steps the structure may differ, but in general our goal is to determine which sets of operations are intended to happen simultaneously. This allows us to compare and analyze demonstrated versus ideal behavior of operations. While a traditional trace visualization relies on the layout of operations to highlight deviations from the ideal, we can compute deviations according to various metrics described in Section 4.

Fig. 1 (right) shows an example logical trace, arranged so that operations that *could* happen simultaneously are vertically aligned, while the left side shows a traditional view. In both visualizations, time proceeds from left to right, but the real-time layout on the left obfuscates the performance problems. Our layout clearly highlights issues by coloring them accordingly, and it makes the relationship between the algorithm and the timing problems more clear. The remainder of this section describes the ordering constraints and layout rules that make this possible.

Lamport Clocks. Logical structure is built upon definitions and relations from Lamport [25]. The *happened-before* relation ($\rightarrow$) is a partial order where (1) for events a, b of the same process, $a \rightarrow b$ if a occurs before b and (2) for matching send and receive events s, r, $s \rightarrow r$. Lamport calls events c, d *concurrent* if they are not ordered, i.e., $c \not\rightarrow d, d \not\rightarrow c$. The *Lamport clock* is a function C mapping a number to each event such that for events a, b, $C(a) < C(b)$ if $a \rightarrow b$. This constraint is called the *clock condition*. Our assigned logical steps satisfy Lamport's clock condition, but we add further constraints when Lamport clocks only provide a partial ordering. Our constraints aim for a more intuitive alignment.

Simultaneous Operations. Rather than assuming that each event happens as early as possible, we aim to discover the operations (paired entry and exit events) that conceptually should happen simultaneously. For example, all send operations at one level of a binomial tree broadcast are conceptually simultaneous. As another example, consider MPI *collectives*. A collective communication operation is one in which all processes in an application must participate at once. Collectives are useful as they allow applications to easily leverage highly optimized implementations of complex, distributed algorithms. We assume all operations in the same blocking collective[1] occur simultaneously. From the developer's point of view, individual calls on each process occur together as a logical abstraction. Rooted collectives like `MPI_Bcast` imply an order between the call on the root and calls on all other participating processes, but we avoid defining collective-internal happened-before rules in order to match the way collectives are invoked.

Phases. It is often intuitive to think of the communication of a program in terms of different *phases*, e.g., a neighborhood exchange or a global reduction (i.e., we assume a very fine grained definition of a phase). To match this intuition, we ensure phases, whether detected by our algorithm or specified by the user, do not overlap. In terms of the clock condition this means that for phases $P \rightarrow Q$ with operations p_i, q_i, respectively, $C(p_i) < C(q_j) \forall p_i \in P, q_j \in Q$. This condition ensures that the ordering within one phase is not affected by other phases.

We focus on communication operations because they impose happened-before relations between processes and thus contribute to a global happened-before structure built from single-process timelines. All other local, per-process events are concatenated into a single operation that covers the entire time between messages. The remainder of this section describes the two steps of logical structure creation: partitioning into phases (or sub-phases) and assigning logical time steps.

3.1 Phase Partitioning

While the primary reason for organizing all communication operations into phases is to match the intuition of program developers with a happened-before relation between phases, this step also has a number of practical advantages. For example, *partitioning* the trace into phases makes the computation and analysis a per-partition rather than a per-trace activity, significantly simplifying and accelerating the analyses of Sections 3.2 and 4. We present graph-based algorithms to first identify inseparable groups of operations and then merge them to define phases. In general, phase detection is a difficult challenge [26], [27], [28], [29], [30], [31], especially since the "correct" partitioning is often subjective or ill-defined. Consequently, we give users the additional option to specify their own partitioning to accommodate application-specific details.

Mandatory Partitions. Our algorithm starts by identifying *mandatory partitions*: groups of operations that cannot be separated due to ordering constraints or semantic reasons. Given a set of MPI operations with their happened-before relations represented as a directed acyclic graph (DAG),

[1] We do not support non-blocking collectives. Hereafter when we refer to 'collectives', we assume them to be blocking.

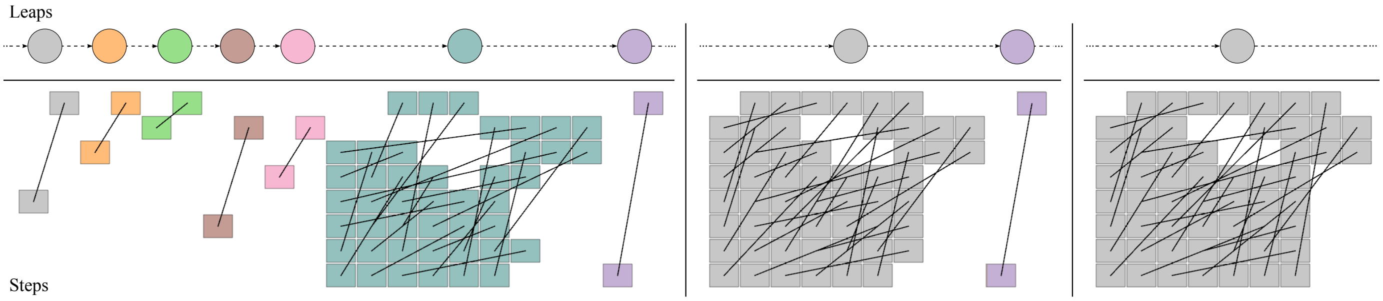


Fig. 3: Merging Leaps in LULESH. The graph in terms of leaps is shown on top. The bottom shows the individual processes as they would be stepped with that leap graph. The result of the strongly connected component merge is the left image. The gray leap merges in its succeeding leaps until it contains all processes, resulting in the center image. The remaining purple leap is significantly closer to the gray leap than the next one (not shown), so it is merged backwards, resulting in the right image.

we construct the partitioning in a bottom-up fashion. We initially assign each operation its own partition (Fig. 2a). Semantically, a matching send and receive, or each *message*, should belong to a single partition, and we merge their corresponding partitions (Fig. 2b). Similarly, the partitions of all operations in the same collective invocation should be merged. These merges can introduce cycles in the graph, as shown in the figure, which prevents a linear ordering among the partitions and thus the ability to applied happened-before ordering between partitions. To restore a linear order we merge all partitions that form a strongly connected component, restoring the partition graph to a DAG (Fig. 2c). The resulting partitions are minimal groups of operations that support a total order without separating messages and collectives. In practice, the resulting partitions are often fine-grained as even simple operations like allreduce can be subdivided significantly. Since this typically does not match the intuition or intent of the developers, we present additional techniques to further merge partitions if desired.

Waitall Partitions. One common construct in MPI applications is `MPI_Waitall`, which causes a process to wait until a given set of prior MPI operations has completed. We merge all partitions containing operations associated with the same `MPI_Waitall` as an additional semantic constraint. If these operations `MPI_Waitall` were not recorded in our traces, we determine the set heuristically and make this merging optional in case the heuristic does not apply. We assume that all calls associated with the `MPI_Waitall` are not interspersed with receive operations or collective, wait, or test calls. Thus, we assume that all send operations between the last such call and an `MPI_Waitall` belong to that `MPI_Waitall`. The reason receive operations are included in the former list is that in the trace any receive call associated with the `MPI_Waitall` ends during that `MPI_Waitall`.

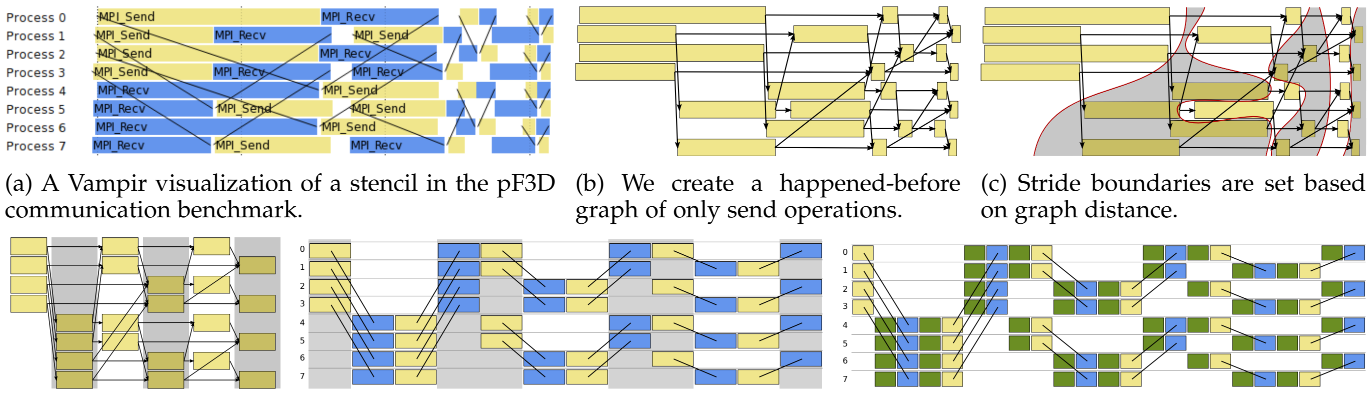
Leap Partitions. There may exist messages that do not result in a strongly connected component in the sense of Fig. 2, yet nevertheless logically belong together as part of the same phase. Fig. 3 shows an example taken from an eight process trace of LULESH [3]. Many of the communication operations have been grouped, resulting in the multi-message blue partition. However, a few messages on either side are isolated and thus are not included. In bulk synchronous codes, such as LULESH, we expect all processes to participate in each communication phase and thus we provide the option to merge partitions until this property is satisfied. More formally, we define a *leap* as all the partitions with the same graph distance from the sources of the partition DAG[2]. We merge partitions until each leap contains operations from all processes using Algorithm 1.

```
complete_leaps (partitions);
    all_leaps = compute_leaps (partitions);
    k = 0;
    while $k < |all\_leaps|$ do
        leap = all_leaps[k];
        changed = TRUE;
        while changed and not complete (leap) do
            changed = FALSE;
            for p in partitions (leap) do
                incoming = leap_distance (p, k-1);
                outgoing = leap_distance (p, k+1);
                if incoming $\ll$ outgoing then
                    merge_into_previous_leap (p);
                    changed = TRUE;
                else
                    for c in children (p) do
                        if will_expand (c, leap) then
                            absorb_partition (p, c);
                            changed = TRUE;
                        end
                    end
                end
            end
        end
        if not complete (leap) and force_merge then
            absorb_next_leap (leap);
        else
            k = k+1;
        end
    end
```

Algorithm 1: Complete leaps through merging partitions.

Starting from the first leap, we determine whether it is complete (contains operations from all processes). Should this not be the case, we begin processing its member partitions. Each partition computes its incoming *leap distance* as the minimum of the first operation entry time for each of its

[2] Intuitively, the leap is similar to *rank* in a graded poset, but we avoid that term due to confusion with MPI ranks.



(a) A Vampir visualization of a stencil in the pF3D communication benchmark.

(b) We create a happened-before graph of only send operations.

(c) Stride boundaries are set based on graph distance.

(d) We use strides to position send operations in logical time.

(e) Send operations are positioned at the end of their stride. Receive operations are filled from the earliest step that meets happened-before constraints.

(f) We insert aggregated operations (green) before each communication operation. Now all real time is represented through operations. We use this property for analysis in Section 4.

Fig. 4: Step Assignment. Send operations are yellow. Receive operations are blue. Alternating white and gray backgrounds denote stride boundaries.

processes and the operation exit time of their previous operation in the partition's previous-leap neighbors. Similarly, its outgoing leap distance is the minimum of the last operation exit time for each of its processes and the operation entry time of the next operation in the partition's next-leap neighbors. By construction, any previous leap is complete and thus we prefer merging at the leap – absorbing un-processed partitions from the next leap – to merging backwards – extending completed leaps. In practice, we only consider merging backwards if the incoming leap distance is more than an order of magnitude (factor of ten) smaller than the outgoing one. Once the direction of a potential merge has been established we always execute a backward merge, but only absorb a partition in from the next leap if this expands the set of processes participating in the current leap. In this manner the current leap can shrink or grow and we repeat this process until the leap stabilizes. Depending on the application, the resulting stable leap may still not contain all processes. In this case we allow the user to either force all corresponding partitions to merge in all their successors before restarting the leap merge algorithm or to accept the incomplete leap and continue.

In the example of Fig. 3, the gray partition on the left successively merges in the succeeding partitions until it has merged in the blue one and thus contains all eight processes. As this completes the leap, the algorithm moves onto the next leap which contains only the purple partition. This partition merges backward since in this case it is significantly closer to the incoming gray one than to the outgoing leap (not shown). The particular threshold to decide the merge direction and whether to force completed partitions should reflect the user's knowledge (or expectations) of the application in order to create the most intuitive partitioning.

Leap merging should be performed when the user suspects that the application generally engages all processes at a coarse scale. This is true in bulk synchronous codes where it is reasonable to assume the partition DAG is a path and each phase would be understood to contain all processes. However, this would also be true in cases where the partition DAG branches, but every process can be assumed to be active in one of the parallel phases. Forcing the merge should be done when the user is very confident all processes are active throughout the trace at phase-granularity.

While the algorithms described above may not accurately detect all phases, they are simple to implement, easy to adapt, and in our experience create intuitive partitions well-aligned with the developer's intention for all practical cases.

3.2 Local and Global Step Assignment

In Section 3.1 we create a DAG of partitions containing related communication operations. Next, we assign logical steps within each partition locally, then globally across partitions, defining the logical structure.
The local step assignment follows three simple principles:

1) All happened-before relationships must be strictly maintained, i.e., $a \rightarrow b$ implies $step(a) < step(b)$;
2) All operations of the same collective invocation happen simultaneously; and
3) Send operations have a greater impact than receive operations on the communication structure.

Item 3 is a consequence of the fact that the order of receive operations is not always uniquely defined by the program and some operations, such as `MPI_Waitall`, may serve as the receiving operation for multiple send operations. Consequently, we initially use only the send and collective operations to define the communication structure. Once the local (per-partition) order for these operations has been determined we introduce the receive operations and ultimately the non-communication operations to the per-partition step assignment. We use an eight process run of the pF3D communication benchmark, shown in Fig. 4, as a working example throughout our explanation.

Strides. The send and collective operations in a trace typically define most of the communication structure and thus we start the local step assignment by grouping these into *strides*. Strides are defined by the graph distances from the beginning of the partition considering only the send and collective operations. More specifically, we create a sparse version of the happened-before graph of each partition that contains only the send operations, collective operations, and their aggregated dependencies (Fig. 4b). To maintain the condition that collectives occur simultaneously, we note that any happened-before dependencies on any individual operation in this collective must be applied to all operations in the collective at this stage. We next group send and collective operations according to their stride (Fig. 4c). We align the strides in logical time and assign preliminary steps accordingly (Fig. 4d). Not all processes contain an operation in all strides.

After send operations are positioned, we re-introduce receive operations so that the ordering is preserved. All send and collective operations within a stride are assigned the same step, and receive operations are placed as early as possible while still maintaining their happened-before relationships (Fig. 4e). Finally, we insert aggregated *non-communication* operations representing all processing between communication operations (Fig. 4f) such as computation or idling.

Defining these aggregated operations allows us to account for all physical time spanned by the trace, which is helpful when defining the temporal metrics in Section 4. To assign global steps, we shift the local step assignment within each partition to be after all the steps occupied by its predecessors in the partition DAG, enforcing global happened-before relationships.

3.3 Isend Coalescing

Throughout our structure extraction pipeline, we have defined an operation to be the matching enter and exit of a single procedure call. However, we have found it useful to optionally coalesce uninterrupted, unbounded sequences of neighboring `MPI_Isend` enter and exit records into a single operation before starting our extraction routine. The resulting operation has an enter time of the first `MPI_Isend` and the exit time of the last. Messages associated with any of the composite calls become associated with the coalesced operation. As individual `MPI_Isend` operations are short and non-blocking, coalescing them can reveal structure that is obscured when processes have different `MPI_Isend` invocation counts without misrepresenting dependencies. In general, we recommend performing coalescing unless the user requires more detail about the individual calls and knows they should be aligned at the level of the individual operation.

Fig. 5 shows the results of our structure extraction for a single partition of an eight process SMG2000 [5] trace with and without coalesced `MPI_Isend`s. In Fig. 5a, the `MPI_Waitall` operation happens at different steps for each process depending on how many messages that process is waiting for (which depends on the part of the boundary the process computes) and where in the order of the sending processes each of those send operations falls. Fig. 5b effectively eliminates these concerns, perfectly aligning all send operations and all receive operations. This depicts the symmetry of the exchange. Encouraging comparisons between like operations without violating ordering is also beneficial when metrics based on these comparisons are applied (see Section 4 and Section 5.3).

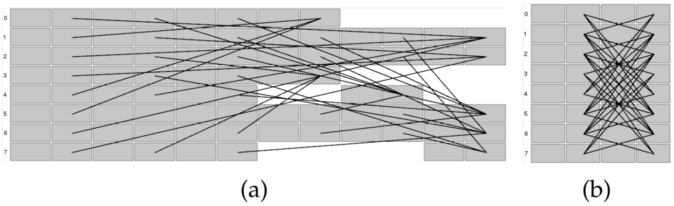


Fig. 5: One partition of an eight process SMG2000 trace, (a) without and (b) with coalescing of `MPI_Isend`s.

4 Temporal Metrics

By design, we avoid relying on wall-clock timing information when determining the logical structure of a trace. This produces a well-aligned version of the trace where the relationship between potentially simultaneous operations is clear. It also avoids problems with clock skew and synchronization. Ultimately, however, the timing of operations determines where delays or bottlenecks occur and which part of the program is responsible. We therefore preserve the temporal information by computing metrics from timestamps. In the visualization, these metrics can be mapped onto the logical structure as highlights. This makes delays easy to see without obscuring the logical layout.

Lateness. Simple metrics, such as the entry time, exit time, or duration of an operation, can be computed directly without the logical structure. However, the true power of our technique comes from comparing such simple per-operation metrics within logical partitions. For example, comparing the exit times of operations in the same logical step allows one to track delays. In particular, we define the *lateness* of an operation as the difference between its own exit time and that of the earliest operation in its step in the partition:

$$l_{op} = op.exit - \min\{x.exit | op, x \in P, x.step = op.step\}$$

where P is the set of operations within a partition. In bulk-synchronous codes leaps typically contain operations from all processes and thus lateness is calculated globally. This can also be enforced by a post-stepping merge across shared global steps. However, for codes with different process-groups that perform separate and distinct actions, the partition ensures that only related operations are compared.

Fig. 6 shows a portion of a 16 process MG trace visualized in Ravel with communication operations colored by the lateness metric. Ravel displays both a traditional physical timeline and a logical timeline. Both views show a delay in a non-communication operation on the first process which propagates to other processes. The logical time view highlights a propagation of lateness along processes and along messages to other processes. This leads us to classify the conditions that contribute to the lateness of an operation depending on whether the operation in question is receiving a message or not. A late, non-receiving operation whose predecessor is not late is likely responsible for the delay, perhaps due to load imbalance in the computation (Fig. 7a). If the predecessor is late as well (Fig. 7b), lateness has been propagated and was likely caused upstream. Similarly, a late receiving operation whose corresponding sending operation is not late (Fig. 7c) indicates that the message has either been delayed in flight, e.g., due to contention in the network,

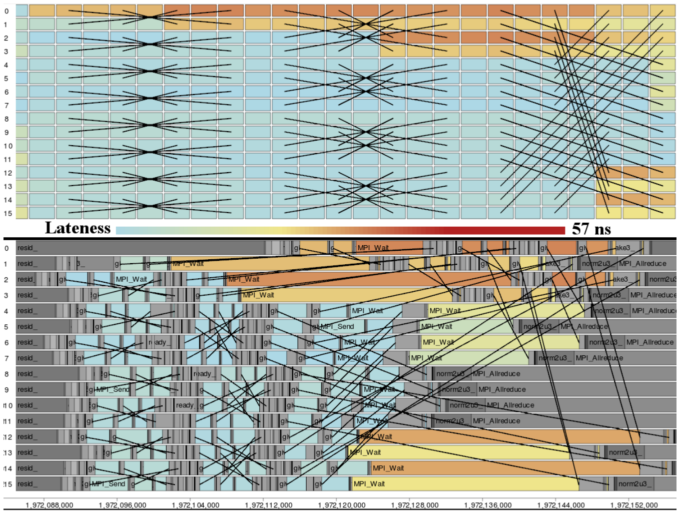


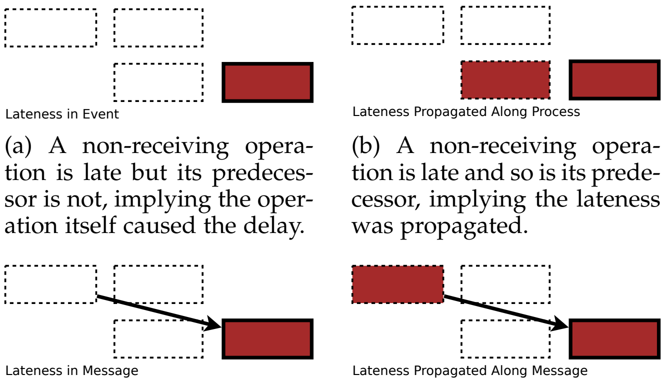
Fig. 6: Logical (top) and physical (bottom) time visualization of a 16 process execution of MG. Communication operations are colored using the lateness metric. The first process becomes late during an aggregated non-communication operation. The lateness spreads through messages to the other processes.

or is late because of the processing needed to perform the receive, which could be caused by, e.g., a slow buffer allocation. Finally, a late receive operation with a matching late send operation indicates lateness propagation across processes (Fig. 7d). The aggregated non-message operations created in global step assignment are necessary to differentiate between in-process and across-process lateness. One interesting and useful property of lateness is that it naturally "resets" once all processes become equally late. For example, a tree-structured reduction rooted at a single process resets lateness, as does a barrier or a simple load imbalance that propagates globally through neighbor exchanges.

Differential Lateness. Lateness provides a good high level overview of potential root causes of delays. Especially when coupled with the visualizations in Ravel, a user can quickly find the first late operation and continue a more detailed analysis from there. However, in very large or complex traces, identifying these patterns becomes challenging, meaning techniques are necessary to directly identify the likely cause of a problem. To this end we propose to analyze *differential lateness*: the difference between the lateness attributed to prior operations and the lateness at exit time:

$$d_{op} = \max\{l_{op} - \max\{l_x | x \to op, \nexists y \text{ s.t. } x \to y \wedge y \to op\}, \\ 0\}$$

Instead of showing all operations that are late, differential lateness highlights the operations and processes that cause the lateness. Note that we do not allow negative lateness: while it can highlight some operations that compensate for earlier problems, negative lateness primarily occurs at reset boundaries leading to confusing and difficult to interpret configurations.


Lateness in Event
Lateness Propagated Along Process
Lateness in Message
Lateness Propagated Along Message

(a) A non-receiving operation is late but its predecessor is not, implying the operation itself caused the delay.

(b) A non-receiving operation is late and so is its predecessor, implying the lateness was propagated.

(c) A receiving operation is late but the corresponding sending operation is not, implying that the lateness was created in flight.

(d) A receiving operation is late and so is its matching send operation, implying that we waited for a late message.

Fig. 7: Creation and propagation of lateness for non-receiving (a,b) and receiving (c,d) operations.

5 Evaluation

We execute applications on two radically different architectures: a large Blue Gene/Q (BG/Q) installation as well as an Infiniband cluster with 12 Sandy Bridge cores per node. In the latter, the cores are split across two sockets, with 6 cores per socket. The BG/Q system uses IBM's compute node kernel OS and IBM's BG/Q MPI implementation. The Infiniband cluster uses a Red Hat derived Linux distribution and the MVAPICH MPI implementation. On both machines we obtain our traces in Open Trace Format 2 (OTF2) [32] using Score-P [33] or Open Trace Format (OTF) [34] using VampirTrace [35].

Our structure extraction algorithm is implemented in Ravel, a desktop application. As our algorithm operates on messaging operations, the number of messages rather than the number of processes or the total time spanned by the trace is the limiting factor in terms of scale. The current implementation is memory bound by the number of messages in the trace due to a preprocessing step which matches messages to operations.

5.1 MPI Collective Operations

Collective algorithms are an important part of MPI because they allow groups of processes to work together for efficient global communication. For example, MPI provides an `MPI_Allreduce` algorithm that performs a distributed parallel sum (or other associative operation) and puts its result on all processes. From a visualization perspective, collectives have dense communication patterns, with many messages sent between processes at around the same time. This poses a challenge for existing trace tools, especially when the system is noisy and dependence chains across MPI processes are perturbed. We use these as a case study of our tool to demonstrate its ability to correctly determine logical structure and to show how we can display collective operations in an intelligible manner. For our experiments, we used libNBC [8], an open source implementation of non-blocking MPI collective operations. We chose libNBC because the algorithms it implements for its collectives are well understood, allowing us to verify our logical structure.

We first consider the binomial tree implementation of `MPI_Allreduce`. Fig. 8 shows the unprocessed trace as visualized by Vampir and its extracted logical structure as visualized by Ravel. The algorithm performs a parallel reduction with a binomial tree embedded in the MPI ranks, then it broadcasts the global sum back along another binomial tree. Our logical structure captures the send-receive operation pairs at each level of the tree, despite the overlap observed in the physical time visualization. All of our partitioning options yield the same logical steps but different partitions. In the figure we show the partitioning resulting from mandatory merging and merging across global steps.

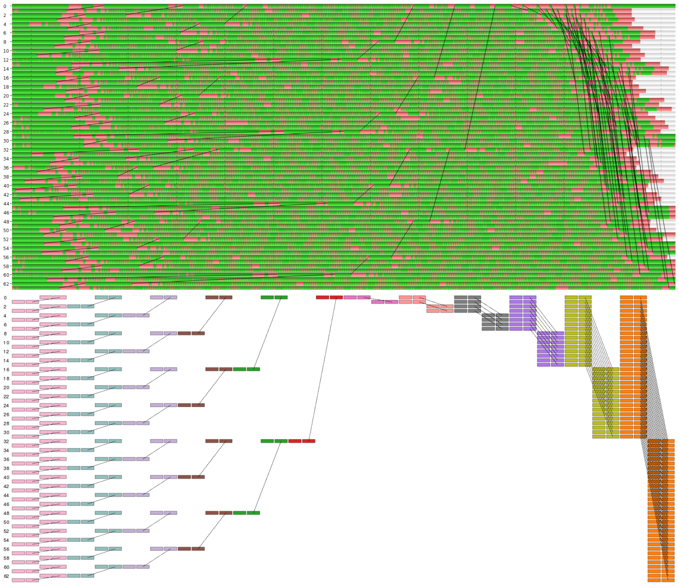


Fig. 8: Visualization of 64 process binomial tree `MPI_Allreduce` in physical time by Vampir (top) and logical time by Ravel (bottom). In logical time, we color by communication partition. We are able to identify the binomial tree levels though they overlap in physical time.

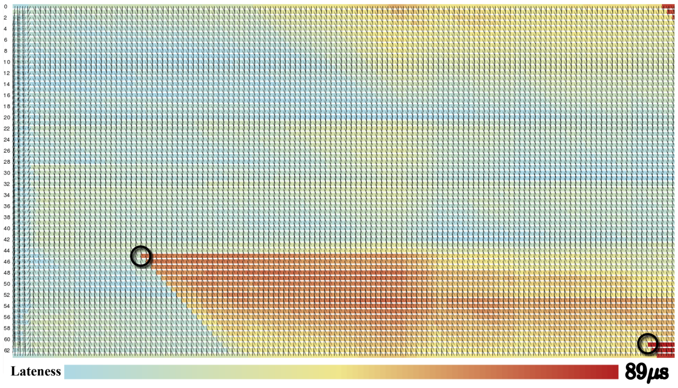


Fig. 9: Ring algorithm `MPI_Allreduce` on 64 processes. Coloring is done by lateness, showing propagation. We find two operations with high differential lateness (circled).

Fig. 9 shows the logical time view of a ring implementation of `MPI_Allreduce`, colored by lateness. In this linear-time algorithm, each of the P processes sends to its neighbor and accumulates a sum from each rank's contribution. Again our logical structure accurately determines the P rounds of this communication. We further observe the spread of lateness from the 45th process and its continued effects through the remainder of the rounds. Also visible are a handful of late processes in the final rounds. The circled steps were the only ones calculated to have high differential lateness, indicating these were the sources of the other delays. Closer examination reveals lateness is injected at a messaging operation, possibly due to congestion on the network.

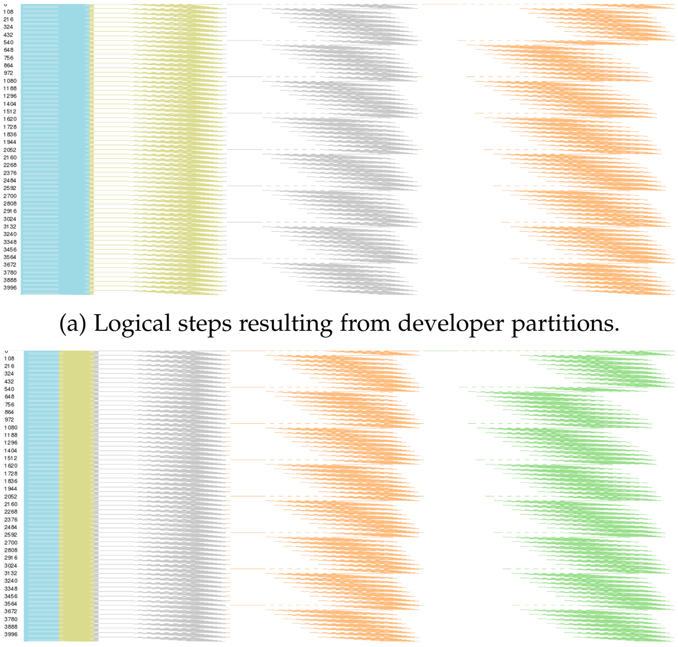
5.2 Massively Parallel Merge Trees

Merge trees are topological structures that can aid in the analysis of very large and complex parallel simulations [36], [37], [38]. We consider a massively parallel algorithm to compute them *in situ* [9], which avoids the limitations and penalties of writing out the data to be analyzed post mortem. Previously, we demonstrated how visual analysis of logical structure helped locate a sub-optimal message ordering in an early version of the merge tree algorithm [2]. Here, we analyze the validity of the logical structure we extract from traces of this code.

In the merge tree algorithm, each process running the simulation must compute its local merge tree over the simulation features of interest. These local merge trees are sent to *gather processes* which combine the local trees and in turn send to the next level gather processes. The algorithm proceeds in these gather rounds until a global merge tree is computed. The gather processes are organized as a k-ary tree, where one process of a set of k siblings at one level acts as the group's gather process at the next level. At the end of each round, the intermediate merge tree is sent not only to this gather process, but also down along the tree to the leaves.

We obtained communication phase information from the developers and compared it to our partitioning using the leap merge and merging across global steps. Fig. 10 shows a 4,096 process, 8-ary merge-tree where operations are colored by membership in their logical partition as determined by the developer in Fig. 10a and our algorithm in Fig. 10b. The main difference is that our algorithm breaks the initial phase into the up (to the gather process) and down (from the gather process) partitions, but even with this difference, the resulting logical structures are highly similar. In both images, the first level of the gather tree structure is apparent from the eight parallelograms stacked vertically in the process space – indicating the eight parallel subtrees.

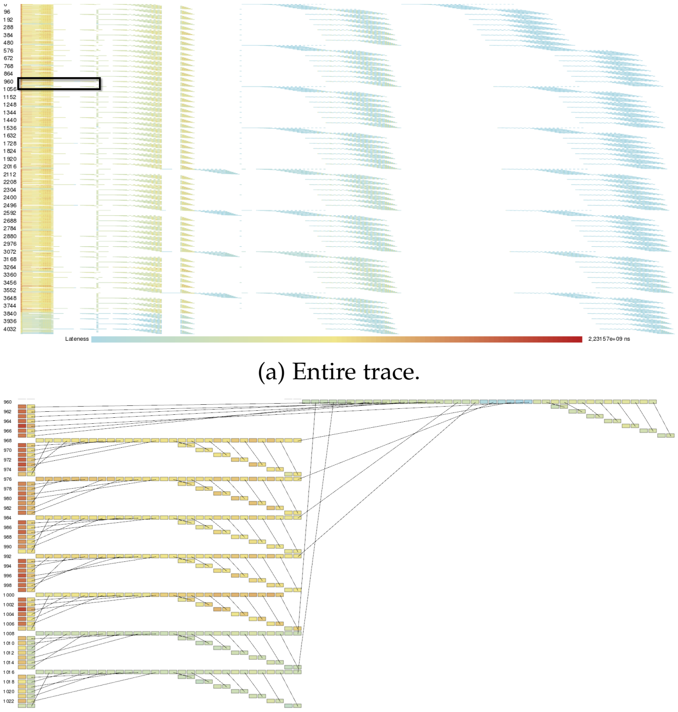
The parallel merge tree algorithm uses asynchronous primitives for its communication. However, an early development version of the algorithm used synchronous primitives. Closer examination of this early implementation reveals some of the shortcomings of a strict adherence to the Lamport happened-before ordering. Fig. 11b shows eight gather groups of eight leaves at the beginning of a 4,096 process, 8-ary merge tree trace with partitioning given by the developers. In the first step, the (level-0) leaves send to their level-1 gather process which responds with corrections and subsequently sends the result to the level-2 gather



(a) Logical steps resulting from developer partitions.

(b) Logical steps resulting from our partitions.

Fig. 10: 4,096 process merge tree, colored by partitioning. In (a) we use partitions from the merge tree developers. In (b) we derive partitions using our algorithm. The partitioning and resulting logical structure are highly similar.



(a) Entire trace.

(b) Detail shows shifting of steps based on happened-before ordering.

Fig. 11: Trace from an older implementation of the merge tree, on 4,096 processes. In (a), the entire merge tree trace is shown colored by lateness. The portion in the black box is shown in more detail in (b). The top gather process receives messages from the gather processes of faster groups. To enforce the true ordering of operations, send operations of the initial gather must be shifted toward the right, preventing logically parallel communication from being assigned the same step.

process. However, the top set of eight leaves is later than its sibling groups for the level-1 gather. The level-1 gather processes of those siblings send their results before the topmost level-1 gather has received all messages from its children. As a result the early receive operation causes a misalignment of the steps with the remaining communication operations of the top-most process being shifted towards the right. We observe this effect amongst multiple gather groups with varying levels of severity, seen as horizontal lines of different lengths in the full view (Fig. 11a) and thus shifting all the send operations back to the leaves several steps to the right. This is a direct consequence of the happened-before ordering and thus cannot be avoided. Nevertheless, in this case the early message does not actually change the order of computation. Thus, potentially allowing the stepping algorithm to violate the happened-before relation to create the expected regular patterns could likely result in a more intuitive visualization and more meaningful metrics. However, it is not clear under which circumstances such a re-ordering should be permissible and this will be the subject of future research.

5.3 Algebraic Multigrid

Algebraic multigrid techniques solve sparse linear systems that may or may not be associated with an actual spatial grid. The method begins with a fine-grained grid or matrix that is successively coarsened until it can be solved with reasonable error. It interpolates back from the coarsened solution to the fine-grained one. This so-called V-cycle is repeated until it has converged. We examine an algebraic multigrid method implemented in the *hypre* scalable solver library [10], via the AMG2013 benchmark, which is part of the CORAL [11] benchmark suite. This gives us an opportunity to verify our structure algorithm for a more complicated example.

Fig. 12 shows a portion of the logical structure we extracted, using the leap merge option, from a 64 process trace of the AMG2013 solver algorithm executed on the BG/Q machine. The operations are colored by partition. Our structure separates the first 54 processes into distinct partitions from the remaining eight. This led us to examine

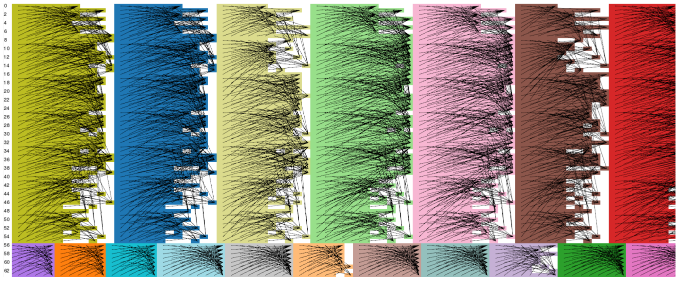


Fig. 12: Partitioning of AMG2013's solver algorithm executed on 64 processes. The last eight processes partition independently of the others.

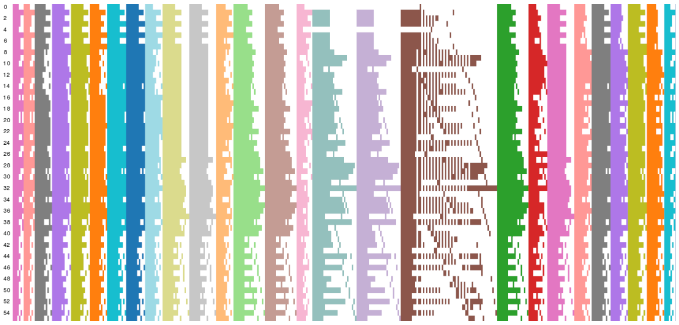


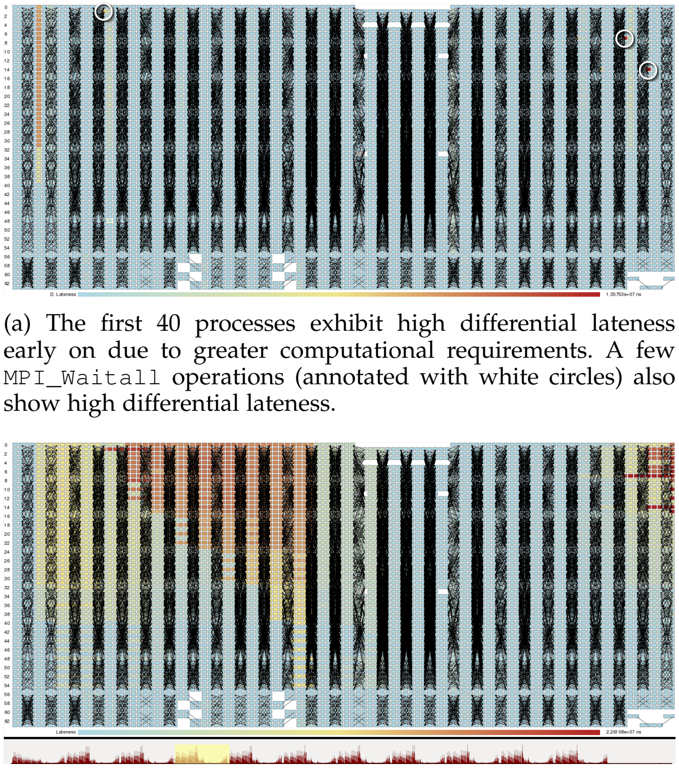
Fig. 13: Partitioning of a single iteration of the AMG2013 solve, focusing on the first 54 processes. The individual partitions match well with what we expect from the levels of the V-cycle. We see the amount of communication increase as processes in coarser levels gain more neighbors. Eventually some processes become inactive due to coarsening, resulting in white gaps across the blue and lavender partitions preceding the brown one.

the rest of the structure and discover that the two process groups never interacted within the solve. Upon consulting with the development team and verifying the results, we learned that the final eight processes are assigned to the anisotropic portion of the domain, which explains why they behave differently and independently, as found by our logical structure.

We narrow our focus to a single iteration, shown in Fig. 13, once again colored by partition. For simplicity we show only the 54 process partition and omit message lines. In the solve, each level performs a relaxation step and one to two matrix-vector products. Our algorithm separates these in partitioning. Initially, the partitions are short, but as the grid gets coarser, participating processes need to send information to more neighbors, resulting in longer partitions representing the increased communication. At the same time, the coarsening leaves some processes without work, seen as white gaps (no operations) across the blue and lavender partitions preceding the long brown one. This behavior is expected, suggesting the logical structure extracted by our partitioning approach is consistent with AMG's algorithm design.

The AMG2013 solve cycle generally uses a sequence of `MPI_Irecv`s, `MPI_Isend`s, and an `MPI_Waitall`. This characteristic makes it a good candidate for isend coalescing (Section 3.3) to examine lateness. Fig 14a shows the operations of a single solve cycle colored by differential lateness. The coarse partitions where some processes are not participating are apparent from the white gaps in the operations across ranks 0 and 4, as well as the denser lines in those steps amongst the other processes that are sending to more neighbors. We observe the first 40 processes exhibit high differential lateness in the computation following the first communication volley, indicating an imbalance. We also note high differential lateness in a few `MPI_Waitall` operations, circled in white.

Examining lateness instead (Fig. 14b), we see the propagation of lateness from these abnormal `MPI_Waitall`s. We also note the lateness overview at the bottom reveals a periodic pattern of lateness over logical time. The number of repetitions corresponds to the number of iterations of the V-cycle reported by the run, indicating this is a recurrent issue.



(a) The first 40 processes exhibit high differential lateness early on due to greater computational requirements. A few `MPI_Waitall` operations (annotated with white circles) also show high differential lateness.

(b) The overview on the bottom shows eleven repetitions of the lateness profile, corresponding to the iterations of the V-cycle. Lateness spreads from the operations of high differential lateness in Fig. 14a.

Fig. 14: Logical structure of an AMG2013 solver cycle on 64 processes.

We focus on one of these `MPI_Waitall` operations in Ravel's physical time view (Fig. 15). The operation is selected in both the logical and physical time views with the associated message lines highlighted in yellow. From our logical steps and lateness metrics, we were able to locate this aberrant ∼12ms `MPI_Waitall` quickly and learn that its expected behavior is like the short `MPI_Waitall` calls before it rather than the longer ones after it. When differential lateness is high for a receiving operation, we expect lateness to be due to the message itself (Fig. 7c). In this case, all the messages come from processes on the same node so the network could not have contributed to the lateness. Furthermore, other `MPI_Waitall` calls complete much more rapidly. We note that the late `MPI_Waitall` does not complete until the next round of `MPI_Waitall`s begin on its senders. This leads us to hypothesize the behavior may be an asynchronous progress issue – the `MPI_Waitall` occurs late enough that the MPI implementation does not handle its matching outstanding `MPI_Isend`s until the next step's `MPI_Waitall`s. We run AMG2013 again, this time setting the `PAMID_ASYNC_PROGRESS` environment variable, which uses a separate thread to make asynchronous progress at the cost of potentially greater latency. The differentially late `MPI_Waitall`s are no longer present in the resulting trace

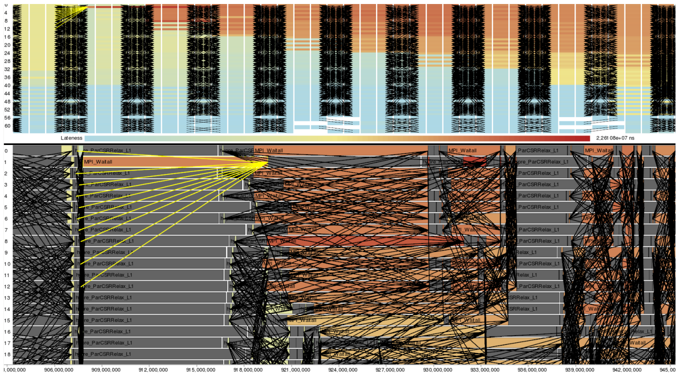


Fig. 15: Ravel logical and physical view of an `MPI_Waitall` with high differential lateness in the AMG2013 solve cycle. Messages to the `MPI_Waitall` are highlighted in yellow.

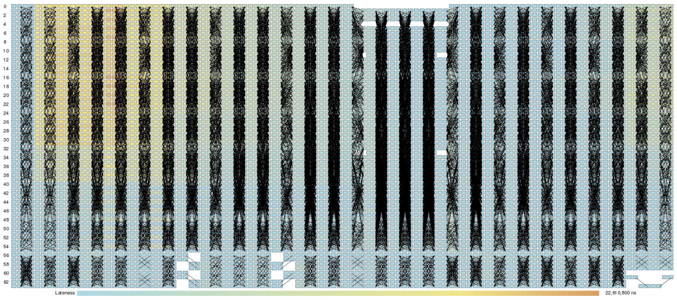


Fig. 16: Logical structure of an AMG2013 solve cycle on 64 processes with an asynchronous progress thread running. Compared to Fig. 14b, the lateness due to `MPI_Waitall`s is gone, leaving only the computation lateness.

(Fig. 16), leaving only computation-based lateness.

6 Conclusion and Future Work

We have presented a new approach for analyzing execution traces obtained from message passing programs. We extract a logical structure, meant to capture the intended ordering of operations in a program. This technique utilizes happened-before relationships not only on the scale of individual events, but also on the scale of communication phases and even concurrent send operations. We explicitly hide timing information in our logical structure to show relationships among operations, and we use temporal metrics mapped onto this structure to highlight timing problems without clutter. In particular, we exploit the logical structure by capturing each event's delay relative to its peers, providing an abstract view of lateness. Using the happened-before relationship encoded in the logical structure, we are able to both pinpoint the original cause of a bottleneck and to study its propagation.

Through a series of case studies, we have demonstrated that our algorithm can identify structures across a variety of communication profiles. We have shown that our metrics correctly pinpoint communication delays and their sources. However, we also exhibited an example where derived structure was non-ideal (Fig. 11), indicating there are cases not covered by our algorithm. In future work, we intend to improve our heuristics for message-passing programs, expand the types of operations and dependencies handled by our structure extraction algorithm, and further leverage logical structure for detection of performance issues.

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