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Improving the Availability of Supercomputer Job Input Data Using Temporal Replication

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Abstract Storage systems in supercomputers are a major reason for service interruptions. RAID solutions alone cannot provide sufficient protection as 1) growing average disk recovery times make RAID groups increasingly vulnerable to disk failures during reconstruction, and 2) RAID does not help with higher-level faults such failed I/O nodes.

This paper presents a complementary approach based on the observation that files in the supercomputer scratch space are typically accessed by batch jobs whose execution can be anticipated. Therefore, we propose to transparently, selectively, and temporarily replicate ”active” job input data by coordinating the parallel file system with the batch job scheduler. We have implemented the temporal replication scheme in the popular Lustre parallel file system and evaluated it with real-cluster experiments. Our results show that the scheme allows for fast online data reconstruction, with a reasonably low overall space and I/O bandwidth overhead.

Keywords Temporal Replication · Batch Job Scheduler · Reliability · Supercomputer · Parallel File System

1 Introduction

Coping with failures is a key issue to address as we scale to Peta- and Exa-flop supercomputers. The reliability and usability of these machines rely primarily on the storage systems providing the scratch space. Almost all jobs need to read input data and write output/checkpoint data to the secondary storage, which is usually supported through a high-performance parallel file system. Jobs are interrupted or rerun if input/output data is unavailable or lost.

Storage systems have been shown to consistently rank as the primary source of system failures, according to logs from large-scale parallel computers and commercial data centers [11]. This trend is only expected to continue as individual disk bandwidth grows much slower than the overall supercomputer capacity. Therefore, the number of disk drives used in a supercomputer will need to increase faster than the overall system size. It is predicted that by 2018, a system at the top of the top500.org chart will have more than 800,000 disk drives with around 25,000 disk failures per year [18].

Currently, the majority of disk failures are masked by hardware solutions such as RAID [15]. However, it is becoming increasingly difficult for common RAID configurations to hide disk failures as disk capacity is expected to grow by 50% each year, which increases the reconstruction time. The reconstruction time is further prolonged by the “polite” policy adopted by RAID systems to make reconstruction yield to application requests. This causes a RAID group to be more vulnerable to additional disk failures during reconstruction [18].

According to recent studies [12], disk failures are only part of the sources causing data unavailability in storage systems. RAID cannot help with storage node failures. In next-generation supercomputers, thousands or even tens of thousands of I/O nodes will be deployed and will be expected to endure multiple concurrent node failures at any given time. Consider the Jaguar system at Oak Ridge National Laboratory, which is on the roadmap to a petaflop machine (currently No. 5 on the Top500 list with 23,412 cores and hundreds of I/O nodes). Our experience with Jaguar shows that the majority of whole-system shutdowns are caused by I/O nodes’ software failures. Although parallel file systems, such

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as Lustre [6], provide storage node failover mechanisms, our experience with Jaguar again shows that this configuration might conflict with other system settings. Further, many supercomputing centers hesitate to spend their operations budget on replicating I/O servers and instead of purchasing more FLOPS.

Figure 1 gives an overview of an event timeline describing a typical supercomputing job's data life-cycle. Users stage their job input data from elsewhere to the scratch space, submit their jobs using a batch script, and offload the output files to archival systems or local clusters. For better space utilization, the scratch space does not enforce quotas but purges files after a number of days since the last access. Moreover, job input files are often read-only (also read-once) and output files are write-once.

Although most supercomputing jobs performing numerical simulations are output-intensive rather than input-intensive, the input data availability problem poses two unique issues. First, input operations are more sensitive to server failures. Output data can be easily redirected to survive runtime storage failures using *eager offloading* [14]. As mentioned earlier, many systems like Jaguar do not have file system server failover configurations to protect against input data unavailability. In contrast, during the output process, parallel file systems can more easily skip failed servers in striping a new file or perform restriping if necessary. Second, loss of input data often brings heavier penalty. Output files already written can typically withstand temporary I/O server failures or RAID reconstruction delays as job owners have days to perform their stage-out task before the files are purged from the scratch space. Input data unavailability, on the other hand, incurs job termination and resubmission. This introduces high costs for job re-queuing, typically orders of magnitude larger than the input I/O time itself.

Fortunately, unlike general-purpose systems, in supercomputers we can anticipate *future* data accesses by checking the job scheduling status. For example, a compute job is only able to read its input data during its execution. By coordinating with the job scheduler, a supercomputer storage system can selectively provide additional protection only for the duration when the job data is expected to be accessed.

Contributions: In this paper, we propose *temporal file replication*, wherein a parallel file system performs transparent and temporary replication of job input data. This facilitates fast and easy file reconstruction before and during a job's execution without additional user hints or application modifications. Unlike traditional file replication techniques, which have mainly been designed to improve long-term data persistence and access bandwidth or to lower access latency, the temporal replication scheme targets the enhancement of short-term data availability centered around job executions in supercomputers.

We have implemented our scheme in the popular Lustre parallel file system and combined it with the Moab job scheduler by building on our previous work on coinciding input data staging alongside computation [28]. We have also implemented a replication-triggering algorithm that coordinates with the job scheduler to delay the replica creation. Using this approach, we ensure that the replication completes in time to have an extra copy of the job input data before its execution.

We then evaluate the performance by conducting real-cluster experiments that assess the overhead and scalability of the replication-based data recovery process. Our experiments indicate that replication and data recovery can be performed quite efficiently. Thus, our approach presents a novel way to bridge the gap between parallel file systems and job schedulers, thereby enabling us to strike a balance between an HPC center resource consumption and serviceability.

Table 1 Configurations of top five supercomputers as of 06/2008

System	# Cores	Aggregate Memory (TB)	Scratch Space (TB)	Memory to Storage Ratio	Top 500 Rank
RoadRunner(LANL)	122400	98	2048	4.8%	1
BlueGene/L(LLNL)	106496	73.7	1900	3.8%	2
BlueGene/P(Argonne)	163840	80	1126	7.1%	3
Ranger(TACC)	62976	123	1802	6.8%	4
Jaguar(ORNL)	23412	46.8	600	7.8%	5

2 Temporal Replication Design

Supercomputers are heavily utilized. Most jobs spend significantly more time waiting in the batch queue than actually executing. The popularity of a new system ramps up as it goes towards its prime time. For example, from the 3-year Jaguar job logs, the average job wait-time:run-time ratio increases from 0.94 in 2005, to 2.86 in 2006, and 3.84 in 2007.

2.1 Justification and Design Rationale

A key concern about the feasibility of temporal replication is the potential space and I/O overhead replication might incur. However, we argue that by replicating selected "active files" during their "active periods", we are only replicating a small fraction of the files residing in the scratch space at any given time. To estimate the extra space requirement, we examined the sizes of the aggregate memory space and the scratch space on state-of-the-art supercomputers. The premise is that with today's massively parallel machines and with the increasing performance gap between memory and disk accesses, batch applications are seldom out-of-core. This also agrees with our observed memory use pattern on Jaguar (see below). Parallel codes typically perform input at the beginning of a run to initialize the simulation or to read in databases for parallel queries. Therefore, the aggregate memory size gives a bound for the total input data size of active jobs. By comparing this estimate with the scratch space size, we can assess the relative overhead of temporal replication.

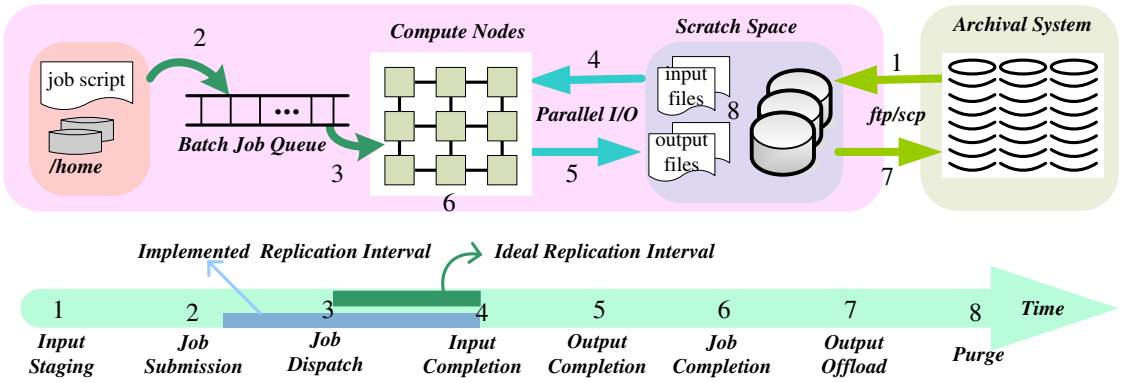

Fig. 1 Event timeline with ideal and implemented replication intervals

Table 1 summarizes such information for the top five supercomputers [22]. We see that the memory-to-storage ratio is less than 8%. Detailed job logs with per-job peak memory usage indicate that the above approximation of using the aggregate memory size significantly overestimates the actual memory use (discussed later in this subsection). While the memory-to-storage ratio provides a rough estimation of the replication overhead, in reality, however, a number of other factors need to be considered. First, when analyzing the storage space overhead, queued jobs' input files cannot be ignored, since their aggregate size can be even larger than that of running jobs. In the following sections, we propose additional optimizations to shorten the lifespan of replicas. Second, when analyzing the bandwidth overhead, the frequency of replication should be taken into account. Jaguar's job logs show an average job run time of around 1000 seconds and an average aggregate memory usage of 31.8 GB, which leads to a bandwidth consumption of less than 0.1% of Jaguar's total capacity of 284 GB/s. For this reason, we primarily focus on the space overhead in the following discussions.

Next, we discuss a supercomputer's usage scenarios and configuration in more detail to justify the use of replication to improve job input data availability.

Even though replication is a widely used approach in many distributed file system implementations, it is seldom adopted in supercomputer storage systems. In fact, many popular high-performance parallel file systems (e.g., Lustre and PVFS) do not even support replication, mainly due to space concerns. The capacity of the scratch space is important in (1) allowing job files to remain for a reasonable amount of time (days rather than hours), avoiding the loss of precious job input/output data, and (2) allowing giant "hero" jobs to have enough space to generate their output. Blindly replicating all files, even just once, would reduce the effective scratch capacity to half of its original size.

Temporal replication addresses the above concern by leveraging job execution information from the batch scheduler. This allows it to only replicate a small fraction of "active files" in the scratch space by letting the "replication window" slide as jobs flow through the batch queue. Temporal replication is further motivated by several ongoing trends in supercomputer configurations and job behavior. First, as mentioned earlier, Table 1 shows that the memory to scratch space ratio of the top 5 supercomputers is relatively low. Second, it is rather rare for parallel jobs on these machines to fully consume the available physical memory on each node. A job may complete in shorter time on a larger number of nodes due to the division of workload and data, resulting in lower per-node memory requirements at a comparable time-node charge. Figure 2 shows the per-node memory usage of both *running* and *queued* jobs over one month on the ORNL Jaguar system. It backs our hypothesis that jobs tend to be in-core, with their aggregate peak memory usage providing an upper bound for their total input size. We also found the actual aggregate memory usage averaged over the 300 sample points to be significantly below the total amount of memory available shown in Table 1: 31.8 GB for running jobs and 49.5 GB for queued jobs.

2.2 **Delayed Replica Creation**

Based on the above observations about job wait times and cost/benefit trade-offs for replication in storage space, we propose the following design of an HPC-centric file replication mechanism.

When jobs spend a significant amount of time waiting, replicating their input files (either at stage-in or submission time) wastes storage space. Instead, a parallel file system can obtain the current queue status and determine a *replication trigger point* to create replicas for a given job. The premise here is to have enough jobs near the top of the queue, stocked up with their replicas, such that jobs dispatched next will have extra input data redundancy. Additional replication will be triggered by job completion events, which usually result in the dispatch of one or more jobs from the queue. Since jobs are seldom interdependent, we expect that supplementing a modest prefix of the queued jobs with a second replica of their input will be sufficient. Only one copy of a job's input data will be available before its replication trigger point. However, this primary copy can be protected with periodic availability checks and remote data recovery techniques previously developed and deployed by us [28].

Completion of a large job is challenging as it can activate many waiting jobs requiring instant replication of multiple datasets. As a solution, we propose to query the queue status from the job scheduler. Let the replication window, w, be the length of the prefix of jobs at the head of the queue that should have their replicas ready. w should be the smallest integer such that:

$$\sum_{i=0}^{w} |Q_i| > max(R, \alpha S),$$

where $|Q_i|$ is the number of nodes requested by the ith ranked job in the queue, R is the number of nodes used by the largest running job, S is the total number of nodes in the system, and the factor $\alpha(0 \leq \alpha)$ is a controllable parameter to determine the eagerness of replication.

One problem with the above approach is that job queues are quite dynamic as strategies such as backfilling are typically used with an FCFS or FCFS-with-priority scheduling policy. Therefore, jobs do not necessarily stay in the queue in their arrival order. In particular, jobs that require a small number of nodes are likely to move ahead faster. To address this, we augment the above replication window selection with a "shortcut" approach and define a threshold T, $0 \leq T \leq 1$. Jobs that request $T \cdot S$ nodes will have their input data replicated immediately regardless of the current replica window. This approach allows jobs that tend to be scheduled quickly to enjoy early replica creation.

2.3 **Eager Replica Removal**

We can also shorten the replicas' life span by removing the extra copy once we know it is not needed. A relatively safe approach is to perform the removal at job completion time. Although users sometimes submit additional jobs using the same input data, the primary data copy will again be protected with our offline availability check and recovery [28]. Further, subsequent jobs will also trigger replication as they progress toward the head of the job queue.

Overall, we recognize that the input files for most in-core parallel jobs are read at the beginning of job execution and never re-accessed thereafter. Hence, we have designed an *eager replica removal* strategy that removes the extra replica once the replicated file has been closed by the application. This significantly shortens the replication duration, especially for long-running jobs. Such an aggressive removal policy may subject input files to a higher risk in the rare case of a subsequent access further down in its execution. However, we argue that reduced space requirements for the more common case outweigh this risk.

3 Implementation Issues

A Lustre [6] file system comprises of three key components: clients, a MetaData Server (MDS), and Object Storage Servers (OSS). Each OSS can host several Object Storage Targets (OST) that manage the storage devices. All our modifications were made within Lustre and do not affect the POSIX file system APIs. Therefore, data replication, failover and recovery processes are entirely transparent to user applications.

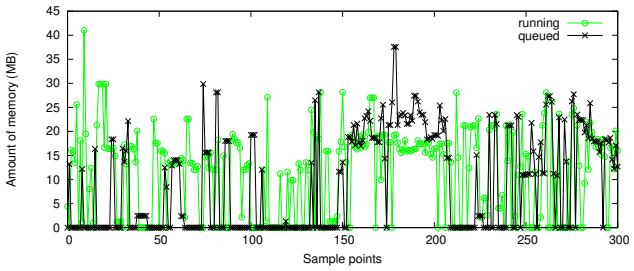

Fig. 2 Per-node memory usage from 300 uniformly sampled time points over a 30-day period based on job logs from the ORNL Jaguar system. For each time point, the total memory usage is the sum of peak memory used by all jobs in question.

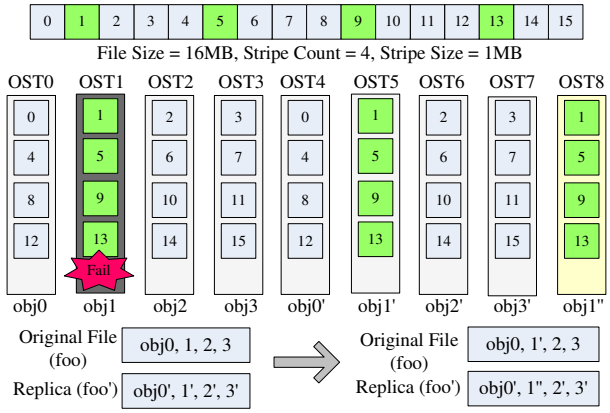

Fig. 3 Objects of an original job input file and its replica. A failure occurred to OST1, which caused accesses to the affected object to be redirected to their replicas on OST5, with replica regeneration on OST8.

3.1 **Replica Management Services**

In our implementation, a supercomputer's head node doubles as a replica management service node, running as a Lustre client. Job input data is usually staged via the head node making it well suited for initiating replication operations. Replica management involves generating a copy of the input dataset at the appropriate replication trigger point, scheduling periodic failure detection before job execution, and also scheduling data recovery in response to reconstruction requests. Data reconstruction requests are initiated by the compute nodes when they observe storage failures during file accesses. The replica manager serves as a coordinator that facilitates file reorganization, replica reconstruction, and streamlining of requests from the compute nodes in a non-redundant fashion.

Replica Creation and Management: We use the copy mechanism of the underlying file system to generate a replica of the original file. In creating the replica, we ensure that it inherits the striping pattern of the original file and is distributed on I/O nodes disjoint from the original file's I/O nodes. As depicted in Figure 3, the objects of the original file and the replica form pairs (objects $(0, 0')$, $(1, 1')$, etc.). The replica is associated with the original file for its lifetime by utilizing Lustre's extended attribute mechanism.

Failure Detection: For persistent data availability, we perform periodic failure detection before a job's execution. This offline failure detection mechanism was described in our previous work [28]. The same mechanism has been extended for transparent storage failure detection and access redirection during a job run. Both I/O node failures and disk failures will result in an I/O error immediately within our Lustre patched VFS system calls. Upon capturing the I/O error in the system function, Lustre obtains the file name and the index of the failed OST. Such information is then sent by the client to the head node, which, in turn, initiates the object reorganization and replica reconstruction procedures.

Object Failover and Replica Regeneration: Upon an I/O node failure, either detected by the periodic offline check or by a compute node through an I/O error, the aforementioned file and failure information is sent to the head node. Using several new commands that we have developed, the replica manager will query the MDS to identify the appropriate objects in the replica file that can be used to fill the holes in the original file. The original file's metadata is updated subsequently to integrate the replicated objects into the original file for seamless data access failover. Since metadata updates are inexpensive, the head node is not expected to become a potential bottleneck.

To maintain the desired data redundancy during the period that a file is replicated, we choose to create a "secondary replica" on another OST for the failover objects after a storage failure. The procedure begins by locating another OST, giving priority to one that currently does not store any part of the original or the primary replica file.[1] Then, the failover objects are copied to the chosen OST and in turn integrated into the primary replica file. Since the replica acts as a backup, it is not urgent to populate its data immediately. In our implementation, such stripe-wise replication is delayed by 5 seconds (tunable) and is offloaded to I/O nodes (OSSs).

Streamlining Replica Regeneration Requests: Due to parallel I/O , multiple compute nodes (Lustre clients) are likely to access a shared file concurrently. Therefore, in the case of a storage failure, we must ensure that the head node issues a single failover/regeneration request per file and per OST despite multiple such requests from different compute nodes. We have implemented a centralized coordinator inside the replica manager to handle the requests in a non-redundant fashion.

[1] In Lustre, file is striped across 4 OSTs by default. Since supercomputers typically have hundreds of OSTs, an OST can be easily found.

3.2 Coordination with Job Scheduler

As we discussed in Sections 1 and 2, our temporal replication mechanism is required to be coordinated with the batch job scheduler to achieve selective protection for "active" data. In our target framework, batch jobs are submitted to a *submission manager* that parses the scripts, recognizes and records input data sets for each job, and creates corresponding replication operations at the appropriate time.

To this end, we leverage our previous work [28] that automatically separates out data staging and compute jobs from a batch script and schedules them by submitting these jobs to separate queues ("dataxfer" and "batch") for better control. This enables us to coordinate data staging alongside computation by setting up dependencies such that the compute job only commences after the data staging finishes. The data operation itself is specified in the PBS job script as follows using a special "STAGEIN" directive:

#STAGEIN hsi -q -A keytab -k my_keytab_file -l user
"get /scratch/user/destination_file : input_file"

We extend this work by setting up a separate queue, "ReplicaQueue", that accepts replication jobs. We have also implemented a *replication daemon* that determines "what and when to replicate". The replication daemon creates a new replication job in the ReplicaQueue so that it completes in time for the job to have another copy of the data when it is ready to run. The daemon periodically monitors the batch queue status using the *qstat* tool and executes the delayed replica creation algorithm described in Section 2.2. These strategies enable the coordination between the job scheduler and the storage system, which allows data replication only for the desired window during the corresponding job's life cycle on a supercomputer.

4 Experimental Results

To evaluate the temporal replication scheme, we performed real-cluster experiments. We assessed our implementation of temporal replication in the Lustre file system in terms of the online data recovery efficiency.

4.1 Experimental Framework

Our testbed comprised a 17-node Linux cluster at NCSU. The nodes were 2-way SMPs, each with four AMD Opteron 1.76 GHz cores and 2 GBs of memory, connected by a Gigabit Ethernet switch. The OS used was Fedora Core 5 Linux x86_64 with Lustre 1.6.3. The cluster nodes were setup as I/O servers, compute nodes (Lustre clients), or both, as discussed later.

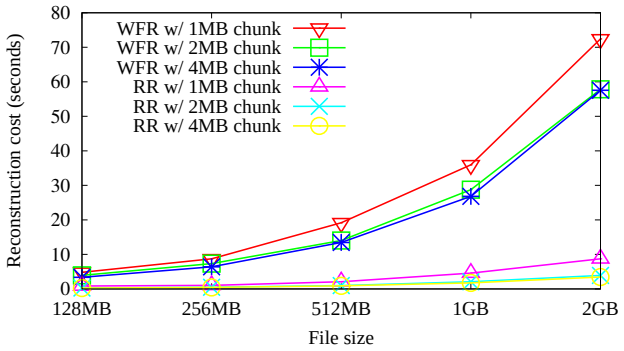

Fig. 4 Offline replica reconstruction cost with varied file size

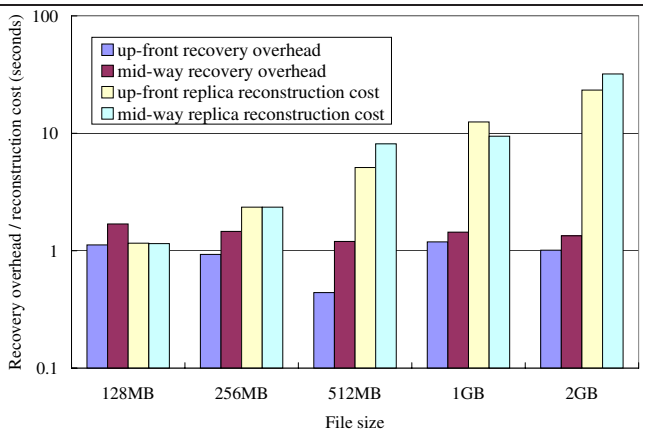

Fig. 5 MM recovery overhead vs. replica reconstruction cost

4.2 Failure Detection and Offline Recovery

As mentioned in Section 3.1, before a job begins to run, we periodically check for failures on OSTs that carry its input data. The detection cost is less than 0.1 seconds as the number of OSTs increases to 256 (16 OSTs on each of the 16 OSSs) in our testbed. Since failure detection is performed when a job is waiting, it incurs no overhead on job execution itself. When an OST failure is detected, two steps are performed to recover the file from its replica: object failover and replica reconstruction. The overhead of object failover is relatively constant (0.84-0.89 seconds) regardless of the number of OSTs and the file size. This is due to the fact that the operation only involves the MDS and the client that initiates the command. Figure 4 shows the replica reconstruction (RR) cost with different file sizes. The test setup consisted of 16 OSTs (1 OST/OSS). We varied the file size from 128MB to 2GB. With one OST failure, the data to recover ranges from 8MB to 128MB causing a linear increase in RR overhead. Figure 4 also shows that the *whole file reconstruction (WFR)*, the conventional alternative to our more selective scheme where the entire file is re-copied, has a much higher overhead. In addition, RR cost increases as the chunk size decreases due to the increased fragmentation of data accesses.

4.3 Online Recovery

4.3.1 Application 1: Matrix Multiplication (MM)

To measure on-the-fly data recovery overhead during a job run with temporal replication, we used MM, an MPI kernel that performs dense matrix multiplication. It computes the standard $C = A * B$ operation, where A, B and C are $n * n$ matrices. A and B are stored contiguously in an input file. We vary n to manipulate the problem size. Like in many applications, only one master process reads the input file, then broadcasts the data to all the other processes for parallel multiplication using a BLOCK distribution.

Figure 5 depicts the MM recovery overhead with different problem sizes. Here, the MPI job ran on 16 compute nodes, each with one MPI process. The total input size was varied from 128MB to 2GB by adjusting n. We configured 9 OSTs (1 OST/OSS), with the original file residing on 4 OSTs, the replica on another 4, and the reconstruction of the failover object occurring on the remaining one. Limited by our cluster size, we let nodes double as both I/O and compute nodes.

To simulate random storage failures, we varied the point in time where a failure occurs. In "up-front", an OSTs failure was induced right before the MPI job started running. Hence, the master process experienced an I/O error upon its first data access to the failed OST. With "mid-way", one OST failure was induced mid-way during the input process. The master encountered the I/O error amidst its reading and sent a recovery request to the replica manager on the head node. Figure 5 indicates that the application-visible recovery overhead was almost constant for all cases (right around 1 second) considering system variances. This occurs because only one object was replaced for all test cases while only one process was engaged in input. Even though the replication reconstruction cost rises as the file size increases, this was hidden from the application. The application simply progressed with the failover object from the replica while the replica itself was replenished in the background.

4.3.2 Application 2: mpiBLAST

To evaluate the data recovery overhead using temporal replication with a read-intensive application, we tested with mpiBLAST [8], which splits a database into fragments and performs a BLAST search on the worker nodes in parallel. Since mpiBLAST is more input-intensive, we examined the impact of a storage failure on its overall performance. The difference between the job execution times with and without failure, i.e., the recovery overhead, is shown in Figure 6. Since mpiBLAST assigns one process as the master and another to perform file output, the number of actual worker processes performing parallel input is the total process number minus two.

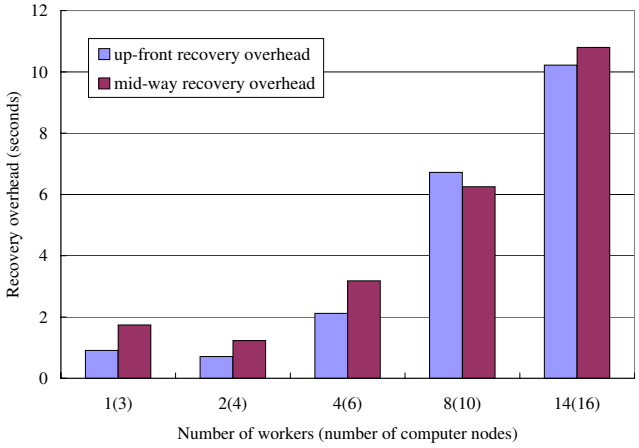

Fig. 6 Recovery overhead of mpiBLAST

The Lustre configurations and failure modes used in the tests were similar to those in the MM tests. Overall, the impact of data recovery on the application's performance was small. As the number of workers grew, the database was partitioned into more files. Hence, more files resided on the failed OST and needed recovery. As shown by Figure 6, the recovery overhead grew with the number of workers. Since each worker process performed input at its own pace and the input files were randomly distributed to the OSTs, the I/O errors captured on the worker processes occurred at different times. Hence, the respective recovery requests to the head node were not issued synchronously in parallel but rather in a staged fashion. With many applications that access a fixed number of shared input files, we expect to see a much more scalable recovery cost with regard to the number of MPI processes using our techniques.

5 Related Work

RAID recovery: Disk failures can often be masked by standard RAID techniques [15]. However, RAID is geared toward whole disk failures and does not address sector-level faults [1,10,17]. It is further impaired by controller failures and multiple disk failures within the same group. Without hot spares, reconstruction requires manual intervention and is time consuming. With RAID reconstruction, disk arrays either run in a degraded (not yielding to other I/O requests) or polite mode. In a degraded mode, busy disk arrays suffer a substantial performance hit when crippled with multiple failed disks [27,20]. This degradation is even more significant on parallel file systems as files are striped over multiple disk arrays and large sequential accesses are common. Under a polite mode, with rapidly growing disk capacity, the total reconstruction time is projected to increase to days subjecting a disk array to additional failures [18]. Our approach complements RAID systems by providing fast recovery protecting against non-disk and multiple disk failures.

Recent work on popularity-based RAID reconstruction [21] rebuilds more frequently accessed data first, thereby reducing reconstruction time and user-perceived penalties. However, supercomputer storage systems host transient job data, where "unaccessed" job input files are often more important than "accessed" ones. In addition, such optimizations cannot cope with failures beyond RAID's protection at the hardware level.

Replication: Data replication creates and stores redundant copies (*replicas*) of datasets. Various replication techniques have been studied [3,7,19,25] in many distributed file systems [4,9,13]. Most existing replication techniques treat all datasets with equal importance and each dataset with static, time-invariant importance when making replication decisions. An intuitive improvement would be to treat datasets with different priorities. To this end, BAD-FS [2] performs selective replication according to a cost-benefit analysis based on the replication costs and the system failure rate. Similar to BAD-FS, our approach also makes on-demand replication decisions. However, our scheme is more "access-aware" rather than "cost-aware". While BAD-FS still creates static replicas, our approach utilizes explicit information from the job scheduler to closely synchronize and limit replication to jobs in execution or soon to be executed.

Erasure coding: Another widely investigated technique is erasure coding [5,16,26]. With erasure coding, k parity blocks are encoded into n blocks of source data. When a failure occurs, the whole set of $n+k$ blocks of data can be reconstructed with any n surviving blocks through decoding.

Erasure coding reduces the space usage of replication but adds computational overhead for data encoding/decoding. In [24], the authors provide a theoretical comparison between replication and erasure coding. In many systems, erasure coding provides better overall performance balancing computation costs and space usage. However, for supercomputer centers, its computation costs will be a concern. This is because computing time in supercomputers is a precious commodity. At the same time, our data analysis suggests that the amount of storage space required to replicate data for active jobs is relatively small compared to the total storage footprint. Therefore, compared to erasure coding, our approach is more suitable for supercomputing environments, which is verified by our experimental study.

Remote reconstruction: Some of our previous studies [23,28] investigated approaches for reconstructing missing pieces of datasets from data sources where the job input data was originally staged from. We have shown in [28] that supercomputing centers' data availability can be drastically enhanced by periodically checking and reconstructing datasets for queued jobs while the reconstruction overheads are barely visible to users.

Both remote patching and temporal replication will be able to help with storage failures at multiple layers. While remote patching poses no additional space overhead, the patching costs depend on the data source and the end-to-end net-

work transfer performance. It may be hard to hide them from applications during a job's execution. Temporal replication, on the other hand, trades space (which is relatively cheap at supercomputers) for performance. It provides high-speed data recovery and reduces the space overhead by only replicating the data when it is needed. Our optimizations presented in this paper aim at further controlling and lowering the space consumption of replicas.

6 Conclusion

In this paper, we have presented a novel temporal replication scheme for supercomputer job data. By creating additional data redundancy for transient job input data and coordinating the job scheduler and the parallel file system, we allow fast online data recovery from local replicas without user intervention or hardware support. This general-purpose, high-level data replication can help avoid job failures/resubmission by reducing the impact of both disk failures or software/hardware failures on the storage nodes. Our implementation, using the widely used Lustre parallel file system and the Moab scheduler, demonstrates that replication and data recovery can be performed efficiently.

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