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Mantle: Efficient Hierarchical Metadata Management for Cloud Object Storage Services

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Abstract

Cloud Object Storage Services (COSSs) are the primary storage backend in the cloud, supporting large-scale analytics and ML workloads that frequently access deep object paths and update metadata concurrently. However, current COSS architectures incur costly multi-round lookups and high directory contention, delaying job execution. Prior optimizations, largely designed for distributed file systems (with least adoption in clouds), do not apply due to COSS-specific constraints like stateless proxies and limited APIs.

`Mantle` is a new COSS metadata service for modern cloud workloads. It adopts a two-layer architecture: a scalable, sharded database (`TafDB`) shared across namespaces and a per-namespace, single-server `IndexNode` consolidating lightweight directory metadata. With a fine-grained division of metadata and responsibility, `Mantle` supports up to 10 billion objects or directories in a single namespace and achieves 1.8 million lookups per second through scalable execution of single-RPC lookups on `IndexNode`. It also delivers up to 58K directory updates per second under high contention by integrating out-of-place delta updates in `TafDB` and offloading loop detection for cross-directory renames to `IndexNode`, both effectively eliminating coordination bottlenecks. Compared to the metadata services of Tectonic, InfiniFS and LocoFS, `Mantle` reduces metadata latency by 6.6-99.1% and improves throughput by 0.07-115.00×. With data access enabled, it shortens job completion times by 63.3–93.3% for interactive Spark analytics and 38.5–47.7% for AI-driven audio preprocessing tasks. `Mantle` has been deployed on Baidu Object Storage (BOS) for over 2 years, a service offered by Baidu Canghai Storage.

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CCS Concepts: • **Information systems → Cloud based storage**; **Directory structures**.

1 Introduction

Cloud Object Storage Services (COSSs) such as Amazon S3 [5], Azure Blob Storage [28], and Google Cloud Storage [14] have become the dominant storage infrastructure in modern cloud environments [41]. They serve as the foundational layer for a wide range of critical workloads, especially in data-intensive domains such as data analytics and machine learning (ML) training and inference. These applications rely heavily on COSSs to store vast datasets and access them frequently and concurrently. As a result, they demand ultra-low latency and high throughput for both resolving object paths and modifying object metadata to maintain job responsiveness and cost efficiency, particularly given the involvement of expensive computing resources like GPUs.

However, meeting these performance demands in COSSs is non-trivial. Modern workloads often operate on deeply nested directory hierarchies with long access paths and involve substantial directory mutation under concurrency. Our analysis of real-world namespaces (§3) reveals that these namespaces are at billion-scale and the average directory depth is around 11 while the maximum is 95. Overall, many concurrent applications access these namespaces simultaneously, driving the peak throughput of a single namespace to several hundred thousand operations per second or more. Across all metadata requests, the path resolution (also known as lookup) dominates execution time, accounting for over 89% of metadata operation latency in some cases. Furthermore, contention in shared directories significantly degrades the performance of directory modification operations like `mkdir` and `dirrename`, throttling the performance of applications such as interactive analytics queries.

Extensive research has focused on metadata optimizations in distributed file systems (DFSs), yet little attention has been paid to COSSs, despite their significantly higher adoption in cloud environments. COSS architectures impose fundamental constraints, such as stateless proxy layers, limited APIs, and the absence of cooperative client logic, render traditional DFS techniques ineffective. Techniques like metadata caching [26, 42, 50] and speculative parallel path resolution [26] rely on tightly coupled designs that COSSs inherently lack. Similarly, relaxed isolation via single-shard updates [8] can reduce directory update contention but fails to fully address the complex coordination patterns in COSS workloads and leaves path resolution performance largely unoptimized.

To address these limitations, we present `Mantle`, a new COSS metadata service designed to provide ultra-low latency, high throughput, and contention-resilient performance. `Mantle` features an inclusive two-layer architecture comprising a scalable, sharded `TafDB` and a lightweight, per-namespace `IndexNode` optimized for fast directory lookups. Unlike prior tiered designs [21], `Mantle` introduces a fine-grained division of metadata and serving responsibilities: `TafDB` stores all metadata at scale and is shared across namespaces, while `IndexNode` caches only essential directory metadata for a single namespace, enabling efficient single-RPC path lookups rather than cross-node, multi-round path traversals.

Beyond its architectural innovations, `Mantle` introduces two key optimizations to meet its performance goals. First, it redesigns the data organization and lookup-serving workflow within `IndexNode` to prevent it from becoming a single-node bottleneck. To reduce CPU overhead, `Mantle` employs the TopDirPathCache, a static cache that stores resolution results for high-stability path prefixes. TopDirPathCache avoids runtime promotion or demotion; instead, stale entries are removed by the Invalidator, a lightweight, lock-free mechanism. This design effectively balances fast lookup performance with efficient cache invalidation, triggered by directory updates. In addition, `Mantle` leverages the Raft-based replication group of `IndexNode` by offloading lookup tasks to follower and learner replicas, distributing the workload and enhancing lookup scalability beyond the leader node.

Second, to address contention in concurrent directory updates, `Mantle` introduces to `TafDB` a novel delta record mechanism that replaces in-place updates with conflict-free appends, significantly reducing transaction aborts and retries under high concurrency. For complex operations like cross-directory renames, Mantle moves loop detection logic to `IndexNode` and uses its local metadata index to perform locking and validation in a single RPC, avoiding costly distributed coordination. Finally, Mantle applies Raft log batching and follower write offloading to sustain the write throughput of `IndexNode` as directory update rates increase.

`Mantle` has been deployed in the Baidu Object Storage for over 1.5 years. We have reported in §7 with rich deployment experience where 19 internal namespaces and billions of objects are managed. In our evaluation, it supports 10 billion entries in a single namespace, achieving 1.89 million lookups per second. Under high contention, it delivers up to 58.8K `mkdir` and 38.0K `dirrename` operations per second. We compare `Mantle` to three modern hierarchical metadata services,

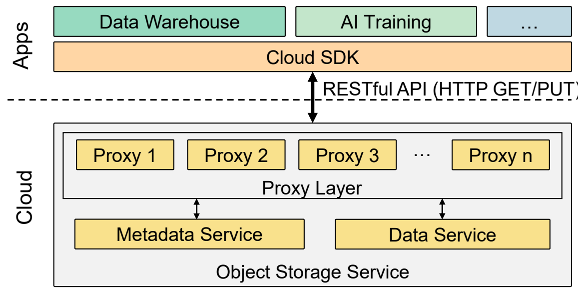


Figure 1. Architecture of typical COSSs with the constrained application interfaces. Note that a single COSS often hosts a number of applications that share the internal metadata and data services.

including Tectonic [33], LocoFS [21], and InfiniFS [26], using two real-world workloads (interactive Spark analytics and AI-based audio preprocessing) and the `mdtest` benchmark. `Mantle` reduces the metadata latency of 17.5-95.2%, 9.5-99.1% and 6.6-98.8%, while introducing throughput speedups of 1.20-20.90×, 1.16-116.00× and 1.07-80.78×, respectively.These improvements translate to 63.3–93.3% shorter job completion times for Spark analytics and 38.5–47.7% for audio preprocessing tasks. `Mantle` and its analysis data will be made available at https://mantle-opensource.github.io/.

In summary, the contributions of this paper are:

- A study of real-world COSS namespaces that identifies critical metadata bottlenecks caused by inefficient lookups and high update contention.
- A two-layer design of `Mantle` that combines a single-node directory index with a scalable database for bulk metadata storage and processing, incorporating optimizations such as metadata division and coordination elimination to avoid single-node bottlenecks.
- An implementation of `Mantle`, incorporating these paradigms, enabling a billion-scale single namespace.
- An in-depth evaluation of `Mantle` using real-world application benchmarks and metadata benchmarks, with comparison against state-of-the-art systems.
- A production deployment of `Mantle` with detailed deployment lessons, offering insights that may inspire future research in the community.

2 Background

2.1 Cloud Object Storage Services (COSSs)

Cloud computing infrastructure investment is projected to account for more than 60% of all global IT infrastructure spending in 2023 [17]. Cloud Object Storage Services (COSSs) have emerged as the primary storage solution for building cloud-based applications. A recent study [41], which examines 396 applications and systems built on Amazon Web Services (AWS), finds that approximately 68% of them use Amazon S3 object storage, whereas distributed file systems are not particularly important and see the least adoption, with only 4% usage. Furthermore, Enterprise Storage Forum reports that the global cloud object storage market was valued at $4.83 billion in 2020 and is projected to reach $13.65 billion by 2028, growing at a compound annual growth rate of 13.6% [40]. This dominant adoption and expanding market highlight COSSs as a critical and timely research focus.

The same study also highlights that two key workloads, analytics and machine learning (ML) tasks, dominate the cloud application landscape. Specifically, over 60% of applications use either analytics or ML services, with analytics accounting for 42% and ML for 18%. Given the growing prominence of AI, ML workloads are expected to continue increasing. COSSs play a vital role in supporting both workloads: analytics engines typically store pre-processed and post-processed data in COSSs like S3, while many ML services—such as those for language and video processing—rely on COSSs to access input data and store output results. These findings are consistent with our observations from an internal cloud environment at a Baidu (see §3 for details).

2.2 COSSs' Interface and Programming Constraints

Figure 1 shows that a typical COSS consists of three key components: a proxy layer, a metadata service, and a data service. The data service maintains a pool of servers to store object data, while the metadata service spans a few servers to manage the object namespace, mapping object paths to their physical data locations.

Typically, a number of applications share a single COSS, where their namespaces and objects are stored in the internal metadata and data services, respectively. COSSs impose constraints on their interactions with applications. Applications interact with COSSs through a restricted set of RESTful APIs [5, 28], typically accessed via cloud SDKs. For example, to retrieve an object, an application issues an HTTP GET request with a specified path to a randomly chosen proxy server. The proxy resolves the path via the metadata service, fetches the corresponding object from the data service, and returns it to the application. Notably, this proxy layer is stateless, which helps with load balancing.

COSSs' loosely coupled architecture strictly isolates their internal components from external users, presenting new challenges for scaling their metadata and data services.

2.3 Metadata Management in COSSs

Metadata performance is crucial for applications using COSSs, because according to the metadata-data separation architecture in Figure 1, metadata services must be accessed before object operations. Furthermore, the application object size is usually small [3, 44], and the metadata overhead has become non-negligible compared to the object accesses. Later, we show that metadata enhancements bring significant application-level performance gains in §6.2.

Recently, many COSSs, including Amazon S3, Azure Data Lake Storage, and Google Cloud Storage, have gradually enhanced their metadata services by transitioning from managing flat namespaces to hierarchical ones [5, 14, 28]. Furthermore, they began to employ databases to handle hierarchical namespaces as database tables, which are sharded and distributed across several servers for scale-out, and orchestrate metadata operations as database transactions [7, 22, 30, 33]. The aforementioned study points out that 16 applications store in DynamoDB [9] pointers to data on S3.

Figure 2 shows the architecture of a DBtable-based hierarchical metadata service of the COSSs of Baidu, similar to that used in the Tectonic [33] storage from Meta. This DBtable-based metadata service maps each hierarchical namespace to a large database table and uses the parent directory's unique ID (`pid`) and object/directory names as primary keys. To achieve load balance while preserving the locality of directories, it further partitions the metadata table by `pid` to place the entries under the same directory within the same shard as possible.

Multi-RPC path resolution. With this architecture, resolving a path to an object or directory involves level-by-level traversal from the root, requiring interaction between the proxy and the metadata service (i.e., the underlying database servers) through multiple rounds of RPCs. This is due to the partitioned nature of the metadata tables, where each directory is stored on a specific database server. At each level, the proxy must retrieve the inode ID of the current directory to compute which server to contact for the next-level lookup. Additionally, permission checks are performed at each step to ensure access control. The top right part of Figure 2 shows that when an application attempts to create a new directory '/A/C/E/G', it first issues an HTTP PUT request to the proxy layer. A randomly selected proxy server then processes this request by recursively traversing the path from the root, validating each component's existence and checking permissions along the way (①, ②, and ③).

Distributed metadata transaction processing. Directory modifications, such as `mkdir` and `dirrename`, require updating metadata entries of more than one directory. When these updates span multiple metadata shards, distributed transactions are needed to ensure strong consistency across the involved database servers [26, 49]. As shown in Figure 2, steps (4a) and (4b) together form a distributed transaction initiated by the proxy to complete the second half of the above `mkdir` request. This transaction coordinates between node3 and node4 to insert the metadata entry for the newly created directory 'G' and to update the metadata of its parent directory 'E' accordingly.

3 Namespace Behaviors of COSSs

To understand the metadata bottleneck of applications atop COSSs, we conduct a detailed analysis of the volume, access characteristics, and performance requirements of namespaces corresponding to data-intensive applications in the

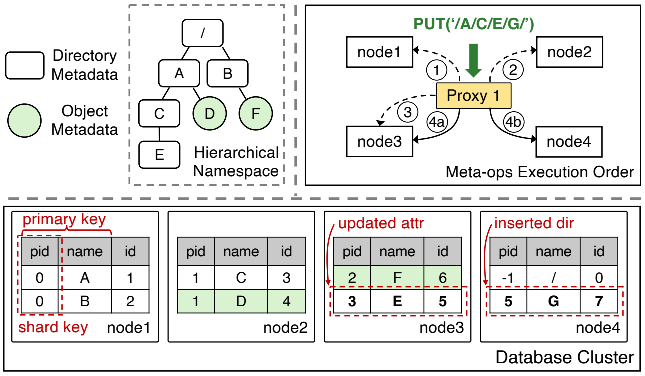


Figure 2. A DBtable-based hierarchical, COSS metadata service. The top left part represents an exemplified namespace containing both directories and objects, with object metadata colored as green. The bottom part depicts the same namespace represented as a table with four shards distributed across four nodes. The top right box shows the execution flow of a `mkdir` request, where dotted arrows stand for retrieving during path resolution, while solid arrows indicate the insertion of new directory metadata plus the mutation on its parent directory's metadata, spanning node3 and node4.

cloud environments of Baidu, where the DBtable-based metadata service has been deployed for years. We profiled five representative namespaces that primarily host workloads like big-data analytic or ML tasks, and the results are summarized in Figure 3 and Figure 4.

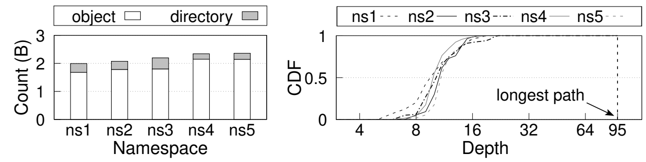
Figure 3a shows that all five namespaces have over 2 billion entries, with objects making up 82.0% to 91.7% and directories only 8.3% to 18.0%. Furthermore, their workloads are characterized by frequent operations on numerous small objects and must sustain a high throughput of 150K to 300K operations per second. Data access to small objects is accelerated by SSDs, reducing latency to a single RPC plus tens of microseconds for device access [1, 4]. As a result, metadata access emerges as a key factor in end-to-end performance.

As an example, in autonomous driving model data preprocessing, multiple tasks process a large dataset of over 1 billion small objects (mostly below 512KB), each encapsulating a short time-span segment of multimodal sensor data and associated metadata collected during vehicle operation. The preprocessing workflow involves scanning existing objects and creating new ones, generating heavy lookup and creation loads. In such scenarios, metadata access dominates total execution time (over 70%).

However, achieving high metadata performance is challenging due to the following two inefficiencies.

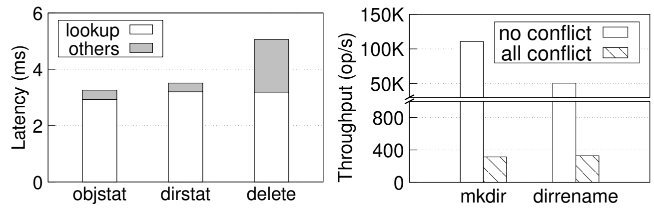
3.1 Lookup Inefficiencies

Surprisingly, these namespaces possess deeply nested directory hierarchies, with average path depths exceeding 10 and maximum depths reaching up to 95. Access patterns from



(a) Object/directory counts **(b)** Request path depths

Figure 3. Characteristics of five real-world namespaces



(a) Latency breakdown **(b)** Throughput

Figure 4. Performance analysis of the DBtable-based COSS metadata service

applications are heavily skewed toward deeper levels of the hierarchy. Figure 3b shows that the average access depths for the five namespaces are 11.6, 11.5, 10.8, 10.6, and 11.9, respectively. For namespace ns4, one of the largest, half of the requests access paths with a depth exceeding 10.

Deep directory hierarchies and long access paths make modern metadata management methods face path resolution bottlenecks. To illustrate this, we analyzed the latency breakdown results of three metadata operations, such as `objstat`, `dirstat`, and `delete`*, by experimenting with the `mdtest` benchmark [39], the DBtable-based metadata service, and 512 application threads (detailed configurations in §6.3). Figure 4a highlights that most of execution time is consumed by the lookup step, i.e., 89.9%, 91.2%, and 63.1% for the three exercised operations, respectively. This long lookup time is contributed by the several rounds of interactions between the proxy layer and the metadata service, as mentioned in §2.3. Note that this conclusion is valid for all other metadata operations (omitted due to space limit), since lookup is the first step of all metadata operations.

3.2 Directory Update Contentions

Directory modification operations, such as `mkdir`, `rmdir` and `dirrename`, constitute a relatively small portion of overall accesses towards a namespace. However, for some applications, they can cause substantial contention on shared directories due to concurrent updates to the same directory attributes.

In our production environment, Spark ad-hoc queries issue over 10,000 runs daily with stringent latency requirements. Each query generates hundreds of subtasks whose temporary directories are atomically renamed into a shared output directory, inducing concentrated metadata updates. Under existing DBtable-based mechanism, the contention causes

*For consistency and clarity, we retain the operation names from `mdtest`.

	Type	#RTTs for lookup	Reduced dir. contention
Metadata caching [26, 42, 50]	DFS	pathlen	N/A
Parallel resolving [26]		[1, pathlen]	N/A
Isolation relaxing [49]		pathlen	restricted
Tiering [21]		single	N/A
Mantle (ours)	COSS	single	all

Table 1. Comparison of metadata services: lookup latency optimizations vs. directory modification contention handling. pathlen denotes the length of the path to be resolved.

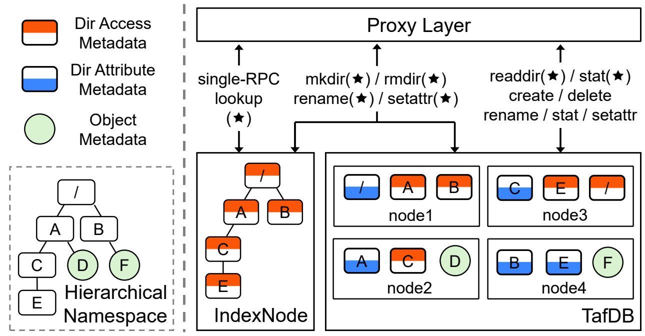


Figure 5. Architecture of the Mantle metadata service and division of metadata request processing over IndexNode and TafDB. Operations marked with (★) are directory operations, while the others are object operations.

frequent transaction retries, turning this commit phase into the primary bottleneck. In extreme cases, it accounts for over 99% of the total task execution time.

To demonstrate the impact of shared directory contention, we additionally ran the mdtest mkdir and dirrename workloads from 512 threads with two cases, where 'no conflict' means all threads write to different directories, while 'all conflict' emulates the above Spark query scenario that writes a single directory. Figure 4b shows that the DBtable-based metadata service performs significantly worse with full contention compared to scenarios without contention, i.e., 99.7% and 99.4% throughput reductions for the two metadata operations, respectively. This degradation occurs because mkdir and dirrename operations trigger distributed two-phase commit transactions across database shards, leading to high abort rates or long lock waiting time under high contention.

3.3 Motivations

In this paper, we aim to build a new metadata service for modern COSSs that delivers ultra-low lookup latency, reduces directory update contention, and maintains high overall metadata throughput. However, as summarized in Table 1, most existing metadata optimization efforts target distributed file systems (DFSs), and they are not directly applicable to COSSs due to fundamental architectural differences.

First, several DFS-based works focus on reducing the number of round-trip times (RTTs) in path lookups. Metadata caching—used in systems like Ceph [50], NFSv4 [42], and InfiniFS [26]—caches directory traversal results to accelerate repeated lookups. While effective in tightly coupled DFS architectures, such caching is difficult to realize in COSSs due to their stateless proxy design, limited API exposure, and lack of cross-layer visibility. Another technique, parallel resolving [26], speculatively predicts and queries metadata shards concurrently across all path levels to reduce average latency. However, under high concurrency, this method becomes counterproductive, as the lookup latency is determined by the slowest request and exacerbated by thread oversubscription. Furthermore, parallel resolving does not reduce the number of RPCs and can not improve throughput capacity of the metadata service. Consequently, resolving a 10-level path with 512 threads in InfiniFS results in an average latency of 7.4 RTTs—approaching that of naïve, sequential resolution in DBtable-based architectures.

LocoFS [21] proposes a tiered metadata service by decoupling directory and object metadata, placing the former on a dedicated directory node and the latter within a scalable database cluster. While this separation theoretically enables independent scaling, it also introduces new challenges. The centralized directory node must handle all directory-related operations, creating a performance bottleneck. Moreover, cross-component coordination is still required for operations like object creation, which involves duplicate name check and parent directory update, both of which must go through the directory node, imposing extra overhead.

Critically, most existing works overlook contention in directory updates, often assuming such operations are infrequent and have negligible impact on overall system performance. This assumption no longer holds in modern COSSs supporting dynamic and high-concurrency cloud workloads. Recent efforts such as CFS [8] attempt to reduce coordination overhead by relaxing isolation levels and transforming distributed transactions into single-shard transactions using atomic primitives. While effective in avoiding coordination for simple directory updates, this strategy breaks down for complex operations like dirrename, which span multiple shards and still incur costly distributed transactions.

In summary, existing approaches either optimize lookup latency or marginally reduce update overheads, but none simultaneously address both in the COSS context. These limitations motivate the design of a new metadata service architecture that holistically enhances COSS performance across diverse and large-scale workloads.

4 Mantle Overview

Figure 5 presents the high-level architecture of Mantle, a new COSS metadata service designed to support a single

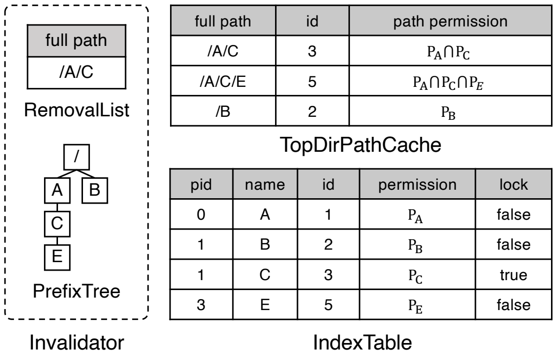


Figure 6. Main data structures on Mantle's IndexNode

namespace containing up to 10 billion directories and objects. Mantle achieves 1.8 million path lookups and 30 thousand directory hierarchy modifications per second, while significantly reducing latency for cloud workloads operating on that namespace. Moreover, by accelerating path lookups, Mantle also improves the performance of all other metadata operations involving both directories and objects.

To enable these capabilities, Mantle is composed of three core components: a proxy layer, TafDB, and IndexNode. As in the DBtable-based metadata service (Figure 1), Mantle's proxy layer receives applications' HTTP requests and coordinates their execution by interacting with the internal components to handle both metadata and data requests. TafDB is a scalable, sharded database responsible for storing metadata at any scale. IndexNode is a dedicated, single-node index that consolidates all/some directory metadata for a given namespace. Each namespace is assigned its own IndexNode, while the shared TafDB remains the scalable backend for all namespaces. This paper focuses on optimizing metadata performance within a single namespace, though the architecture naturally supports multi-namespace deployments by deploying multiple IndexNode instances.

In contrast to the above tiering method, Mantle employs an inclusive, two-layer architecture between IndexNode and TafDB with fine-grained metadata division. While TafDB retains complete metadata, IndexNode maintains only a critical subset of directory metadata (approximately 80 bytes per directory) for efficient lookups and cross-directory coordination. We partition directory metadata into access metadata (red-topped boxes in Figure 5) and attribute metadata (blue-bottomed boxes), with IndexNode storing only the access metadata. As shown in Figure 6, this is implemented through the IndexTable in IndexNode, which includes: parent directory ID (pid), directory name (dirname), directory ID (id), access permissions (permission), and a lock bit for concurrent update coordination.

To complement our data division, we design a fine-grained responsibility split that minimizes IndexNode workload while maximizing TafDB's scale-out capacity for directory operations. As shown in Figure 5, IndexNode handles lookup and permission checks as single-RPC operations, while TafDB processes both object metadata and directory operations (readdir and stat) using its stored attribute metadata. For complex mutations (e.g., mkdir and rename), coordination occurs across both components: TafDB updates all metadata (access and attribute) while IndexNode refreshes access data for future lookups, maintaining strong synchronization. Additionally, IndexNode manages rename loop detection, a particularly challenging task for TafDB when directories span multiple database shards.

The introduction of IndexNode does not alter the availability guarantees of the MetaTable, which is ensured by the underlying database. Therefore, our focus lies on ensuring high availability for the IndexNode itself. This is achieved through the adoption of Raft consensus protocol [31] to replicate updates to multiple nodes. Within the Raft group, all nodes maintain identical in-memory data structures, which are independently constructed by each node according to the procedures described in §5.1.

While these design choices enable scalable metadata management, they also introduce specific challenges that must be addressed to ensure the system's overall performance and consistency. We will elaborate on these challenges together with our solutions next.

5 Design of Mantle

5.1 Scaling Single-RPC Lookup

While the IndexNode centralizes distributed lookups to a single node, the CPU-intensive path resolution process creates a performance bottleneck in IndexNode. This is because the single-RPC lookup on IndexNode still breaks down into several local accesses to IndexTable. Note that this bottleneck becomes more pronounced as the path depth deepens. To this end, we introduce the novel TopDirPathCache design that effectively reduces the CPU consumption in IndexNode (§5.1.1). Following this, to maintain cache coherence with low overhead, we propose a lightweight cache invalidation mechanism that minimizes interference with lookup requests (§5.1.2). Finally, in the Raft group of IndexNode, follower nodes are typically idle, performing only replication tasks, which wastes the CPU resource. Therefore, whether we can use follower nodes to share the path resolution pressure of leader becomes another key to lookup optimization. Detailed designs are provided in §5.1.3.

5.1.1 TopDirPathCache. We design a lookup cache, named as TopDirPathCache, within the IndexNode to alleviate the load on the IndexTable by storing path resolution results. The cache efficiency makes fundamental trade-offs between memory consumption, performance improvement and cache maintenance overhead. Caching every path is infeasible due to excessive memory requirements. For instance, 1 billion directory entries would require over 1TB memory usage. Furthermore, maintaining cache consistency incurs non-trivial overhead: any modification to ancestor directories requires invalidating affected entries, imposing additional CPU burden on the IndexNode. Therefore, we prefer the cached path resolution results highly stable.

Empirical analysis of production traces indicates that most directory rename operations occur near the leaf nodes of the namespace hierarchy. Therefore, we decide not to cache the resolution results of the full path. Instead, we cache only the truncated prefix of the path, keeping some distance from the leaf nodes. Doing so minimizes memory footprint and the overhead of frequent maintenance operations such as promotion and demotion. As shown in Figure 6, TopDirPathCache is implemented as an in-memory hash table, where each entry maps a full path prefix to the pid of the corresponding directory and its aggregated permission mask. Following the Lazy-Hybrid approach [6], permissions along the path are intersected to compute a unified path permission.

The workflow works as follows. Specifically, when handling a lookup request of depth N, IndexNode truncates the final k levels and consults TopDirPathCache using the resulting prefix. The empirical constant k represents the distance from the leaf level beyond which caching is disabled. Consequently, all paths within k levels of leaf nodes are omitted from the TopDirPathCache. As an illustration, when resolving the path '/A/C/E/G/H' with $k = 3$, the prefix '/A/C/' is inspected in TopDirPathCache. If no corresponding entry is found, a new entry for this prefix will be created following path resolution via IndexTable. Evaluations in §6.5 demonstrate that $k = 3$ strikes a balance between performance gains and memory consumption. Specifically, this configuration yields a significant speedup while consuming only 12% of the memory required for caching all results.

5.1.2 Alleviating Lookup-Modification Tension. Directory modifications, such as dirrename and setattr, can render related cache entries stale. Specifically, all entries prefixed by the affected path must be invalidate and removed from TopDirPathCache. This requires a range scan to identify all descendants of the affected directory. However, hash tables, which underlie TopDirPathCache, do not natively support range scanning. Additionally, a coordination mechanism is needed to prevent incoming lookups from accessing the affected range, ensuring consistency.

To coordinate lookups and directory modifications, Mantle introduces Invalidator, a lightweight mechanism for cache invalidation. It relies on two auxiliary data structures, namely PrefixTree and RemovalList. PrefixTree is a lock-free radix tree that rebuilds the directory tree of all cached paths in TopDirPathCache, enabling efficient range queries for invalidation. RemovalList is a lock-free skiplist that records the full paths of directories being modified. These two data structures are populated as follows. Upon new lookup results are cached in TopDirPathCache, PrefixTree is synchronously updated to reflect the new paths. When

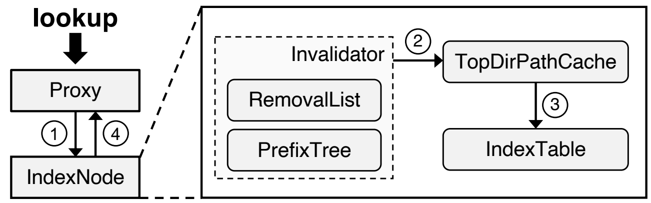


Figure 7. The workflows for processing lookup operation

a directory modification happens (e.g. dirrename and setattr), the target directory's full path is inserted into RemovalList. A background execution thread in Invalidator periodically polls RemovalList, queries PrefixTree to obtain the range of affected paths, and removes the corresponding entries from TopDirPathCache. For rmdir, the target directory can be safely removed without updating RemovalList, as an empty directory cannot be the prefix of an existing directory, eliminating potential conflicts from insertion. The lock-free design of the Invalidator reduces the CPU overhead associated with maintaining consistency, while its non-blocking architecture minimizes contention during lookup operations. These optimizations enable IndexNode to sustain high throughput for path resolution, even under heavy directory modification workloads.

The new lookup workflow on an IndexNode involves interactions with several data structures. As shown in Figure 7, a lookup request begins by scanning RemovalList to check if any paths being modified are prefixes of the requested path. (①). This scan is lightweight and incurs negligible overhead, as RemovalList is empty most of time. If such paths are found, the search skips TopDirPathCache and directly queries IndexTable to avoid accessing stale cached results (③); Otherwise, the request proceeds to search in TopDirPathCache for the truncated prefix path (②). If the prefix is cached, the request resolves the remaining descendant directories through a level-by-level path traversal in IndexTable (③). Upon completing the lookup, TopDirPathCache caches the resolved results of the truncated prefix if the following two conditions meet: (a) the truncated prefix is not cached and (b) RemovalList is not modified during the execution of the lookup request. To detect conflicts between concurrent modifications and the lookup, a conventional timestamp mechanism is used. Finally, the pid of the requested path is returned to Proxy (④).

5.1.3 Path Resolution on Followers/Learners. To overcome the resource limitation of a single node, we offload path resolution requests to idle IndexNode followers when the leader node is under heavy load. A follower first queries the leader node for the latest commitIndex to ensure consistency and avoid stale read. Afterwards, it waits until its local applyIndex exceeds commitIndex before executing local path resolution routine. To minimize the overhead imposed

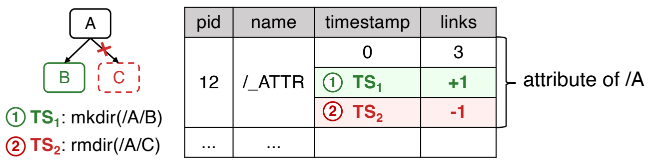


Figure 8. Using delta records avoids contention between different directory modifications within a directory.

on the leader, queries for the `commitIndex` are batched. Additionally, learners (read replicas) [20] are added to the Raft group to further enhance throughput. Both followers and learners maintain and utilize their local `TopDirPathCache` independently to accelerate path resolution.

However, follower read also risks reading stale entries in their local `TopDirPathCache`. To avoid it, cache invalidation is synchronized within the Raft group by replicating invalidation information through the Raft logs. Operations requiring cache invalidation append the full paths of affected directories to the Raft logs. When these logs are applied, the corresponding cache entries are invalidated using the `Invalidator` mechanism described earlier. This approach ensures that followers and learners remain consistently updated with changes to the directories without incurring high overhead.

5.2 Scaling Directory Modifications

There are three key cases to address for improving directory modification performance. First, as observed in §3.2, concurrent modifications to the same directory—particularly those that update its attribute metadata—can cause repeated transaction aborts and retries, resulting in high tail latency. To mitigate this issue, we introduce an out-of-place update mechanism that eliminates attribute contention (§5.2.1). Second, we optimize cross-directory `dirrename`, the most complex metadata operation. In particular, we leverage `IndexNode` to transform loop detection from a distributed coordination task into a local operation (§5.2.2). Finally, as directory modifications become significantly more efficient, we must ensure that `IndexNode` can sustain the increased write load. To this end, we introduce targeted mechanisms to prevent write throughput from becoming bottlenecked by the capacity of a single Raft group (§5.2.3).

5.2.1 Delta Record and Compaction. When concurrent directory operations (such as `mkdir` and `rmdir`) act on the same directory, they often compete for the directory attribute metadata, triggering transaction aborts. This results in frequent retries and increased tail latency. In CFS [49], contention for `mkdir` and `rmdir` is mitigated by splitting each operation into two single-shard transactions: one to insert or delete attribute metadata, and another to update both the access metadata and the parent directory's attribute metadata. However, in our system, this particular two-transaction strategy is incompatible with the synchronization requirements between the `IndexNode` and `TafDB`.

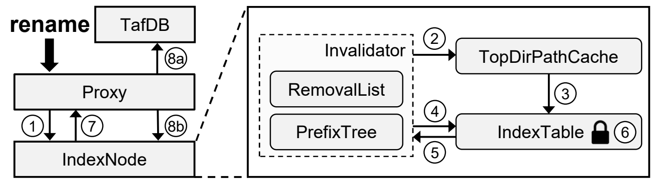


Figure 9. The workflows for processing directory rename operation

Instead, `Mantle` introduces delta records to avoid in-place updates and thereby mitigate contention. As illustrated in Figure 8, each delta record is identified by a composite key composed of the parent directory ID (pid), a special name field ('/_ATTR'), and a transaction timestamp (TS_{txn}). Rather than updating the primary attribute record (the one with timestemp=0) directly, each operation simply inserts a distinct delta record. For example, in Figure 8, a mkdir(/A/B) and a concurrent rmdir(/A/C) both need to modify /A's attribute metadata. Without delta records, these operations would collide on the same row. With delta records, however, the `mkdir` inserts one delta (with TS_1 and +1 to the link count), and the `rmdir` inserts another (with TS_2 and -1), eliminating the conflict. These delta records are later asynchronously compacted into the main directory attribute metadata, with a shared latch ensuring that the directory metadata remains intact and cannot be deleted during the compaction process. This deferred update strategy eliminates contention, significantly reducing transaction aborts, retries, and tail latency in high-concurrency environments.

Despite its advantages, this design introduces a trade-off: `dirstat` operations must scan delta records to compute accurate results. To address this, delta records are enabled selectively, activated only under sustained contention within a directory. This approach effectively reduces contention and improves overall latency. The performance benefits of these two optimizations are demonstrated in §6.4.

5.2.2 Improving Cross-Directory `dirrename`. `Mantle` designates `IndexNode` as the coordinator for cross-directory `dirrename`. Each directory metadata entry in `IndexTable` contains a lock bit, enabling `Proxy` to lock directories involved in a `dirrename` request via a single RPC (see Figure 6). This approach eliminates the need for multiple RPCs to acquire distributed locks.

The cross-directory `dirrename` workflow, illustrated in Figure 9, begins with path resolution (①, ②, ③). `IndexNode` adds the source directory path to `RemovalList` (④) and performs loop detection by setting the lock bit of the source directory path in `IndexTable` (⑤). It then examines the lock status of directories along the path from the least common ancestor of both the source directory and destination directory to the destination directory (⑥). The results of path resolution and loop detection are returned to `Proxy` (⑦). If an existing lock is detected, indicating a conflict with another ongoing rename, the operation aborts and retries. If no conflict is found, Proxy finalizes the dirrename through a distributed transaction, updating all related metadata in both MetaTable and IndexTable (8a and 8b). The rename lock is automatically released when the access metadata of the source directory is deleted in IndexTable.

5.2.3 Improving Raft Write of IndexNode. Under heavy directory modification workloads, the write throughput of an IndexNode is often constrained by the capacity of a single Raft group. This limitation primarily arises from the overhead introduced by frequent fsync operations required to persist data to disks, posing a significant bottleneck during intensive workloads. To mitigate this bottleneck, Mantle employs a batched Raft submissions mechanism, aggregating multiple operations into a single submission. By batching operations, Mantle effectively decreases the frequency of costly fsync calls, reducing disk I/O overhead and significantly improving throughput under high-intensity workloads.

5.3 Fault Tolerance

Mantle 's design incorporates robust mechanisms to guarantee metadata consistency and high availability in the event of component failures.

For metadata server failures, the affected Raft group automatically initiates leader re-election. Integrity and availability are intrinsically preserved by the Raft protocol.

When a proxy becomes unresponsive, clients reconnect to another proxy and resubmit pending requests. To ensure idempotence, each metadata request carries a unique client-generated UUID. As illustrated in Figure 9, if a proxy fails during steps 1–7, the IndexNode retries these steps while leveraging the UUID to recognize if a lock was already held by the original attempt, thereby avoiding deadlocks. If loop detection succeeds, the new proxy continues with steps 8a/8b as normal execution to commit the 2PC transaction and release the lock. If the crash occurs during steps 8a/8b, standard 2PC recovery resolves the final commit decision, ensuring the system reaches a consistent state.

6 Evaluation

6.1 Experimental Setup

Hardware configuration. We conduct experiments in a local cluster of 53 physical servers, each with 128GB DRAM and running CentOS 6.3 (Kernel 4.14.0). Of these, 21 servers are used for metadata services and 32 serve as clients to generate testing workloads. Three metadata servers are equipped with dual sockets Intel(R) Xeon(R) Platinum 8350C processors for Mantle's IndexNode, LocoFS's directory metadata server and InfiniFS's rename coordinator, operating at 2.60GHz with 64 cores, and each has a 1TB NVMe SSD. The remaining servers use dual socket Intel(R) Xeon(R) Silver 4314 CPUs at 2.40GHz with 32 cores, each paired with eight 4TB NVMe SSDs. All servers are inter-connected with Mellanox ConnectX-5 25Gbps. Table 2 presents the evaluation deployment for these four metadata systems. All deployments share the same data storage (using extra data servers).

Table 2. Deployment configurations

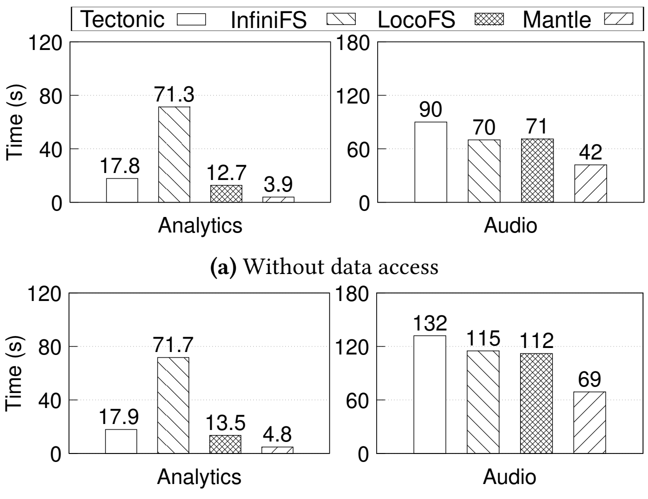
Systems	Metadata	Client
Tectonic	21× servers	32× servers
InfiniFS	3× servers for rename coordinator + 18× servers for metadata	
LocoFS	3× servers for directory metadata + 18× servers for object metadata	
Mantle	3× servers for IndexNode + 18× servers for TafDB	

Baselines. We compare Mantle against three representative baselines: Tectonic, LocoFS and InfiniFS, which exemplify the DBtable-based approach, tiering, and parallel resolving, respectively. We re-implement them faithfully since they are not public. For Tectonic, we relax the consistency and avoid using distributed transactions. In InfiniFS, we adopt CFS's two transactions strategy for directory modification operations. Additionally, we implement AM-Cache from InfiniFS for metadata caching and assess its effectiveness under real-world workloads. Our evaluation shows that the performance of the re-implemented baseline systems aligns with the results reported in their original papers.

Workloads. We evaluate metadata service performance using real-world workloads and adapt mdtest benchmarks to generate heavy-load operations, including object creation (create), object deletion (delete), metadata retrieval (objstat, dirstat), directory creation (mkdir) and renaming (dirrename). These workloads use an average path depth of 10. Throughput is measured via mdtest, with internal and client-side latencies logged. For parallel processing, we employ OpenMPI 5.0.2 to initiate mdtest processes on client nodes. Notice that data storage is only used in application evaluations (§6.2). All other evaluations involve only metadata, which is the focus of this paper. Prior to running experiments, we use mdtest to populate each system with data, scaling the namespace size to 1 billion entries with an object-to-directory ratio of 10:1.

6.2 Application Evaluation

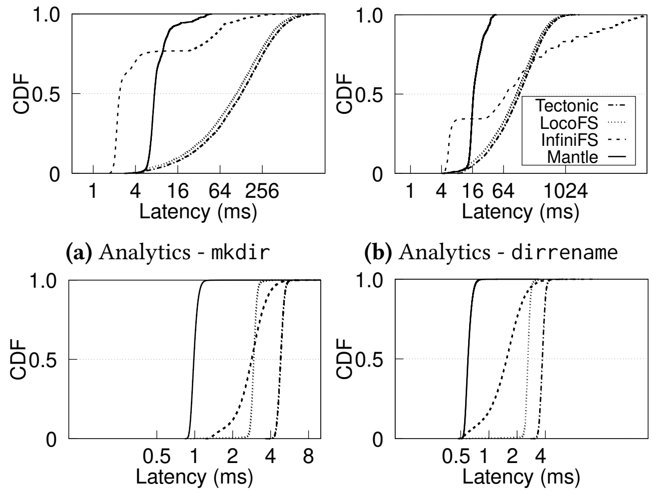
We use two applications to test the performance improvements that Mantle brings to real-world applications. The AI-oriented audio pre-processing (**Audio**) that processes long audio inputs by dividing them into segments that are seconds long, involving a total of 200GB of data. Spark analytics (**Analytics**) performs interactive data analytics involving 10GB of data and includes extensive metadata operations. At first, we cut out data access and record the completion time. Then, we re-enable the data access and record the end-to-end



(a) Without data access

(b) With data access

Figure 10. Completion time of real-world workloads



(a) Analytics - `mkdir` **(b)** Analytics - `dirrename`

(c) Audio - `create` **(d)** Audio - `objstat`

Figure 11. CDF of latency of metadata operations in application workloads when doing only metadata operations

completion time. Meanwhile, we select representative metadata operations in each application and show their latency distribution in Figure 11.

Figure 10a illustrates the completion time of two workloads when data access is disabled. In the Analytics workload, all directory modification operations target the same attribute of the temporary directory, leading to severe conflicts. Tectonic's completion time is 75.0% longer than InfiniFS due to the lack of consistency guarantee in the implementation of Tectonic's directory modification operations. In contrast, InfiniFS employs distributed transactions to ensure consistency, but its `dirrename` performance is impaired by massive transaction retries due to contention. As shown in Figure 11b, 10.6% of its `dirrename` operations experience latencies exceeding 5 seconds, with a peak latency of 52 seconds. LocoFS further reduces the completion time by 27.0%, yet its completion time remains 225% longer than `Mantle`. Although LocoFS avoids conflicts in distributed transaction, modifications to the same key in sub-directory list are serialized by a latch, limiting performance. The CDF curves of `mkdir` and `dirrename` in LocoFS and Tectonic are remarkably similar, as illustrated in Figure 11a and Figure 11b. LocoFS exhibits a slight advantage by completing these operations on a centralized node.

Unlike the Analytics workload, the Audio workload consists only of non-conflicting metadata operations, highlighting the path resolution performance. Tectonic performs the worst on account of its low efficient level-by-level path resolution approach. InfiniFS performs slightly better, reducing completion time by 23.9%, though it does not achieve a significant improvement. This is because the substantial number of sub-threads generated by speculative path resolution results in considerable latency variability.

As shown in Figure 11c and Figure 11d, the latency distribution of InfiniFS metadata operations is broad. While a small portion of `objstat` operations achieve latencies close to `Mantle`, its tail latencies are notably high. LocoFS's single-node path resolution design lacks optimizations to scale up the central node, resulting in increased latencies in path resolution and a completion time comparable to InfiniFS. In contrast, `Mantle` reduces the completion time by 40.8% compared to LocoFS. The CDF curves further demonstrate that `Mantle` achieves high efficiency in these operations.

Finally, Figure 10b presents the completion time of the two workloads when data access is enabled. For the Analytics workload, metadata operations dominate the completion time, resulting in minor difference compared to the time when data access is disabled. This is because enabling data access reduces blocking time by overlapping data access with the previously necessary blocking period. `Mantle` reduces the completion time by 73.2%, 93.3% and 63.3% compared to Tectonic, InfiniFS, LocoFS, respectively. The Audio workload, however, experiences a significant increase in completion time, diminishing `Mantle`'s relative improvement. Nevertheless, `Mantle` reduces the completion time by 47.7%, 40.1% and 38.5% compared to Tectonic, InfiniFS, LocoFS, respectively.

6.3 Individual Namespace Operations

We use `mdtest` with 512 clients to evaluate performance across seven key operations: `create`, `delete`, `objstat`, `dirstat`, `mkdir`, `rmdir`, and `dirrename`. These are grouped into: (1) object and directory read operations (`create`, `delete`, `objstat`, `dirstat`) and (2) directory modification operations (`mkdir`, `rmdir`, `dirrename`). We measure throughput and latency for each operation and perform a latency breakdown

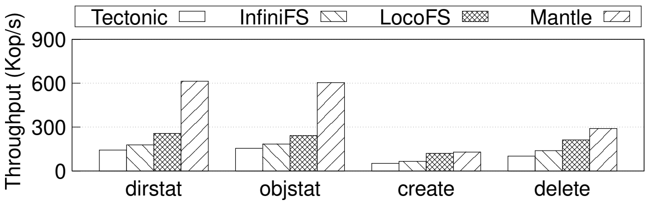


Figure 12. Throughput of object operations and directory read operations

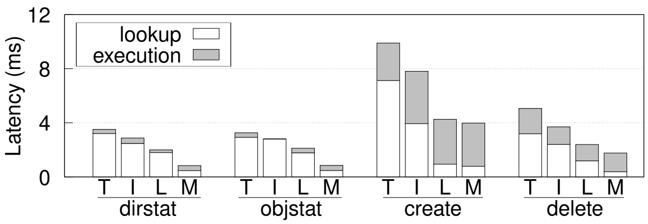


Figure 13. Latency breakdown of object operations and directory read operations (T represents Tectonic, I represents InfiniFS, L represents LocoFS, M represents Mantle)

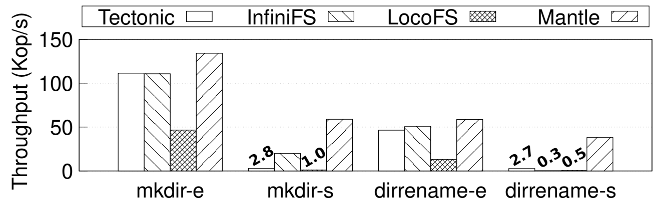


Figure 14. Throughput of directory modification operations

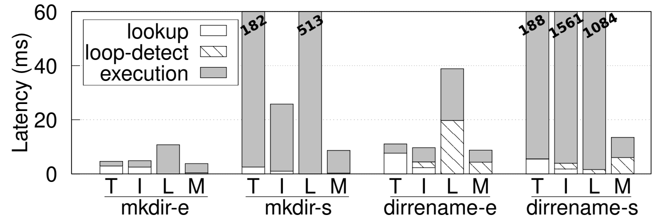


Figure 15. Latency breakdown of directory modification operations (T represents Tectonic, I represents InfiniFS, L represents LocoFS, M represents Mantle)

into three phases: (1) lookup (path resolution), (2) loop detection (optional), and (3) execution. The lookup phase retrieves the directory ID (`pid`). Loop detection, which is only applicable during `dirrename` operations, identifies and resolves potential directory loops. Execution phase allows the metadata service to read or update metadata using the `pid`. InfiniFS bypasses execution phase for `objstat`, handling it in lookup phase, while LocoFS resolves paths during execution phase for directory operations. `Mantle` records zero lookup time in `dirrename` since its merged with loop detection.

Object and directory read operations. Figure 12 and 13 illustrates the performance of object and directory read operations, which is primarily determined by the efficiency of path resolution. Thus, the performance trends are similar across all operations, ranked from worst to best as Tectonic, InfiniFS, LocoFS, and `Mantle`. Tectonic exhibits the lowest performance due to its high overhead in layer-wise path traversal. InfiniFS, while outperforming Tectonic, achieves only a marginal improvement of 0.19-0.37×, attributed to thread over-provisioning in parallel resolving. LocoFS further enhances throughput by 0.32-0.83× compared to InfiniFS, with its centralized path resolution design effectively reducing path traversal overhead. However, its scalability is constrained as local record retrieval exhausts CPU resource of the directory metadata server. `Mantle` achieves the highest performance with the help of `TopDirPathCache` and follower read, maintaining the lowest path resolution latency across all four operations.

`Mantle` introduces significant performance improvements over other baseline systems in `dirstat`, `objstat` and `delete` operations. For `create`, LocoFS achieves comparable throughput to `Mantle`. This similarity is due to data layer modifications in the `mdtest` benchmark, which incurs additional attribute updates to the metadata. These updates reduce the path resolution workload, thereby narrowing the performance gap between LocoFS and `Mantle`.

In conclusion, `Mantle` reduces lookup latency by 83.9-89.0%, 80.0-84.2% and 16.4-74.5%, over Tectonic, InfiniFS and LocoFS, respectively, achieving speedups of 2.49-4.30×, 1.96-3.44× and 1.07-2.50×.

Directory modification operations. We use `mdtest` to evaluate directory modification operations under both conflicting and non-conflicting workloads. In conflicting workloads (suffix '-s'), threads operate on a shared directory, while in non-conflicting workloads (suffix '-e'), each thread uses its own exclusive directory. Results for `rmdir` are omitted as they are similar to `mkdir`.

As shown in Figure 14 and 15, in `mkdir-e`, the throughput of Tectonic and InfiniFS are very close. Tectonic performs slightly better during the execution phase, while InfiniFS shows a slight advantage in the lookup phase. As a result, their overall performance is similar. Both systems are constrained by metadata server bottlenecks under saturated read (for lookup) and write (for rename) requests. LocoFS's throughput is throttled by the Raft throughput, resulting in the worst performance among these systems. `Mantle` achieves the highest throughput with a shorter lookup phase compensating for its longer execution phase. `Mantle`' throughput is bound to a single Raft group and requires further optimizations to scale. Nevertheless, based on our production experience (see §7), its current throughput capacity is sufficient for our deployment needs.

In `mkdir-s`, modifications to the parent directory's attribute are serialized by a latch in both Tectonic and LocoFS. While InfiniFS applies single-shard atomic primitives to avoid retries, its performance still falls short compared to non-conflicting scenario. `Mantle` improves the throughput

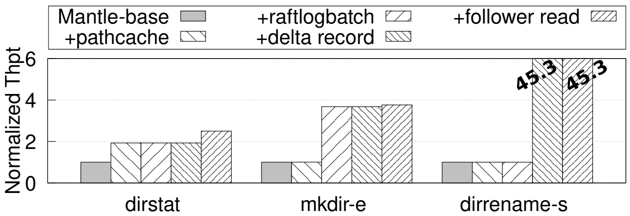


Figure 16. Effects of individual optimization

by 1.96× over InfiniFS using delta records, which enable fully concurrent updates to the directory's attributes.

For `dirrename-e`, the trends are similar to those observed in `mkdir-e`, but two key differences emerge: (1) `dirrename` requires two rounds of path resolution, enlarging the performance gap; (2) loop detection overhead incurs additional overhead in InfiniFS, LocoFS, and `Mantle`. Consequently, `Mantle` achieves 26.2% higher throughput than Tectonic. Loop detection increases the pressure on the central node for both LocoFS and `Mantle`, with LocoFS showing the lowest performance. `Mantle` mitigates extra overhead through its optimized `dirrename` procedure, achieving the highest throughput despite higher loop detection costs. In `dirrename-s`, the performance of Tectonic, InfiniFS and LocoFS degrade significantly due to conflicts. `Mantle` eliminates conflicts using delta records, achieving the highest performance.

In conclusion, `Mantle` demonstrates significant performance improvements in directory modification operations, achieving speedups of 1.20-20.9×, 1.16-116.00×, and 2.87-80.78× over Tectonic, InfiniFS and LocoFS, respectively.

6.4 Effects of Individual Optimization

We evaluate the impact of each optimization by progressively enabling them. We start with the base configuration of `Mantle` (`Mantle`-base), where `TopDirPathCache` is disabled. The '+pathcache' configuration activates in `TopDirPathCache`, enhancing `Mantle`'s efficiency. Subsequent enhancements include '+raftlogbatch' and '+delta record', which respectively implement Raft log batching and delta records. Finally, '+follower read' enables follower read in Raft to accelerate lookup. We test these configurations using three `mdtest` workloads: `dirstat`, `mkdir-e`, and `dirrename-s`.

Figure 16 reports the normalized throughput to `Mantle`-base. The '+pathcache' optimization effectively doubles the throughput of `dirstat`, which is further improved by the '+follower read' optimization. The throughput of `mkdir-e` in `Mantle`-base is constrained by the commit speed of the Raft logs in `IndexNode`. The '+raftlogbatch' optimization takes effect by amortizing the commit overhead. In `Mantle`-base, `dirrename-s` incurs lots of conflicts, leading to failures and retries of database transactions. The '+delta record' optimization eliminates these conflicts and boosts the throughput.

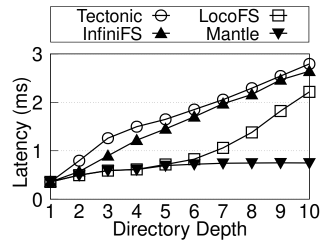


Figure 17. Impact of depth on path resolution

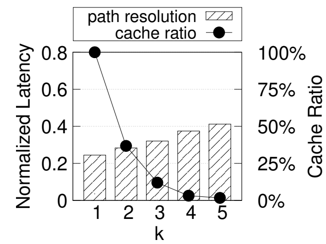


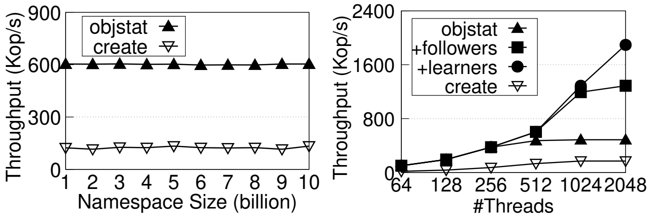
Figure 18. Impact of k in `IndexNode`

6.5 Study of Other Factors

Impacts of depth on path resolution. We evaluate the path resolution latency across various directory depths to assess the impacts on system performance. We initiate 512 threads in 32 servers to send lookup requests. As depicted in Figure 17, the path resolution latencies of Tectonic and InfiniFS escalate with increasing directory depth. Notably, for a ten-level path, the latency for Tectonic and InfiniFS is 6.82× and 6.4× higher, respectively, than that of a single-level path. Tectonic's lookup latency exhibits a linear increase relative to path depth, primarily due to the latency associated with sequentially dispatching an equivalent number of RPCs. In contrast, InfiniFS experiences a bottleneck at greater depths due to thread over-provisioning. LocoFS shows comparable lookup latency to `Mantle` up to a path depth of 6, where CPU limitations become a bottleneck. In comparison, `Mantle` exhibits remarkable stability, with its lookup latency for a ten-level path being only 1.09× higher than that of a single-level path, demonstrating its superior scalability and efficiency.

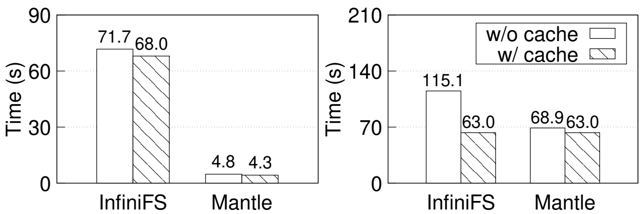
Impact of k in `TopDirPathCache`. We disable follower read and evaluate the impact of k in `TopDirPathCache` by running 512 threads to issue lookup requests and measuring the latency across different k values, ranging from 1 to 5. We also analyze the namespace ns4 (see §3) and calculate the portion of directories that could be cached under different k settings. As shown in Figure 18, the lookup latency increases with larger k values. At $k = 3$, the value chosen in our system, the normalized (to `Mantle`-base) latency is 0.32, 31.1% slower than the latency of $k = 1$. However, the memory consumption is reduced by 88% compared to $k = 1$. In production, we set $k = 3$ to balance between performance and memory usage.

`IndexNode` scalability. We evaluate `Mantle`'s scalability by running `mdtest`'s `objstat` and `create` workloads while varying the size of namespace and number of threads. Initially, we conduct experiments using 512 threads, varying the namespace size from 1 billion to 10 billion entries, and present the results in Figure 19a. The throughput remains consistent regardless of the increasing namespace size, demonstrating `Mantle`'s capability to handle namespaces of up to 10 billion scale effectively. Next, we assess `Mantle`'s scalability with respect to the number of threads by varying the



(a) w.r.t. namespace size **(b)** w.r.t. number of threads

Figure 19. Mantle's scalability w.r.t. namespace size or the number of concurrent clients



(a) Analytics **(b)** Audio

Figure 20. Impact of adding metadata caching

client count from 64 to 2048 on a 10 billion namespace. To analyze the impact of follower read, we evaluate the `objstat` workload under 3 configurations: no follower read (objstat), follower read with 2 followers (+followers) and follower read with additional 2 learner replicas (+learners).

As shown in Figure 19b, the throughput of `create` workload scales linearly up to 512 threads, reaching 18.8 Kop/s at 64 threads and 133.5 Kop/s at 512 thread. However, as the thread count increases to 1024, the throughput rises by only 28.3%, constrained by `TafDB` reaching its maximum capacity. For the `objstat` workload, throughput achieves 101.6 Kop/s and 376.5 Kop/s at 64 and 256 threads, respectively, but levels at 512 threads due to the capacity limitations of a single node. Beyond 1024 threads, no further throughput increase is observed. In contrast, enabling follower read with 2 followers allows `objstat` to scale beyond 512 threads, achieving a throughput of 1288.0 Kop/s with 2048 threads. Adding two learner replicas further enhances scalability, enabling `objstat` to achieve 1894.5 Kop/s at 2048 threads.

Adding metadata caching. Although metadata caching isn't adopted in `Mantle`'s design, we evaluate its effectiveness for potential scenarios outside `Mantle` 's primary focus, where it may still be applicable. We equip InfiniFS and `Mantle` with metadata caching and measure its performance on two real-world applications. Figure 20 illustrates the impact of metadata caching on the performance of InfiniFS and `Mantle` across the Analytics and Audio workloads. For the Analytics workload, metadata caching results in a modest improvement. This limited improvement is due to the nature of the Analytics workload, which is dominated by directory modifications. In contrast, for the Audio workload,

Name	#object	#dir.	Ratio of Small Obj.	Peak Thpt. (Kop/s)	
				lookup	mkdir
C1	3.2B	27M	62.0%	400	24
C2	2.1B	194M	29.2%	300	12
C3	1.2B	145M	33.7%	350	18
C4	0.8B	88M	28.8%	175	11
C5	75M	9M	28.1%	215	9

Table 3. Characteristics of 5 namespaces in Cluster-C. Small object means object with size ≤ 512KB.

metadata caching delivers substantial performance improvements. InfiniFS sees a significant reduction in execution time from 115.1 seconds to 63.0 seconds. `Mantle` also benefits from caching, with its execution time reduced from 68.9 seconds to 63.0 seconds. However, the relative improvement for `Mantle` is smaller, as it already implements an efficient single-RPC path resolution mechanism, leaving less room for optimization through metadata caching.

7 `Mantle` in Production

7.1 Deployment Overview

`Mantle` has been integrated with the legacy COSS system, replacing its DBtable-based metadata management. The new COSS system supports both flat and hierarchical namespaces simultaneously, forming a unified storage foundation.

`Mantle` and the COSS system have been deployed across three clusters (A, B, and C), hosting 19 internal namespaces and numerous external namespaces. These internal namespaces are distributed 7, 7, and 5 across clusters A, B, and C, respectively. Within each cluster, all namespaces share a common `TafDB` deployment. These namespaces serve different application domains, comprising both metadata-intensive tasks (e.g., AI data preprocessing, ad-hoc SQL queries) and I/O-intensive tasks (e.g., model checkpointing, batch analytics). These workloads generate average daily metadata request volumes of tens of billions.

7.2 Lessons and Experiences

Prevalence of Small Objects. To provide a detailed analysis of production workloads, we focus on the five representative internal namespaces hosted in Cluster C, which correspond to our AI training (C1-C3, C5), data warehouse (C2, C3), advertising (C2-C3), finance processing (C3), log analysis (C3, C5) and search engine (C2-C4) workloads. Table 3 summarizes their characteristics. These namespaces represent a spectrum of use cases, from mature, billion-scale workloads (C1-C3) to rapidly growing services (C4, C5). A key workload characteristic across these namespaces is the prevalence of small objects (≤512 KB), ranging from approximately 30% to over 60% for C1. High proportion of small objects indicates many workloads are inherently metadata heavy and can benefit from Mantle's low-latency path resolution. Under these real-world conditions, the system delivers peak lookup throughputs of 175–400 Kop/s and peak mkdir throughputs of 9–24 Kop/s for these namespaces. These production peaks represent only a fraction of Mantle's full throughput capacity, leaving significant headroom for future workload growth.

Co-locating IndexNode for resource utilization. High single-node throughput of IndexNode enables an efficient operational strategy: co-locating IndexNode from multiple namespaces on shared hardware to maximize resource utilization. Specifically, we maintain a shared pool of physical servers to host the IndexNode replicas for all namespaces. Within the pool, leaders of smaller namespaces (e.g. C4, C5) can share a node, while leaders of large, high-traffic namespaces can be assigned exclusive nodes. To avoid hotspots, we adopt a dynamic mechanism to rebalance leader distribution and add new physical nodes on demands.

Impact across workload profiles. Mantle's performance impact is highly dependent on the workload profile, with metadata-intensive applications benefiting the most. For example, the end-to-end completion time of our data preprocessing task described in §3.1 drops by over 40% after migrating to Mantle. In contrast, I/O-intensive workloads experience no performance regression while still benefiting from accelerated lookups. Beyond application-level acceleration, Mantle's high efficiency provides operational benefits by reducing the number of metadata servers required.

Optimization potential. Our profiling shows that Mantle's scalability is currently constrained by the CPU resource of IndexNode. Further optimizations that reduce CPU usage can extend Mantle 's capacity to handle future workload growth without major architectural changes. For example, a proof-of-concept implementation demonstrates that adopting RDMA in the RPC framework can boost per-node path resolution throughput from 500K ops/s to 1M ops/s.

8 Related Work

Metadata management. Early distributed file systems decouple metadata from data and store metadata in a centralized metadata server [13, 16, 24, 29, 32]. To improve scalability, numerous architectures distribute metadata across multiple servers [11, 25, 45, 50, 51, 55]. Recently, in addition to the aforementioned systems, CalvinFS [47], ADLS [37], HopsFS [30] and λFS [7] leverage distributed databases for metadata management.

Different metadata partitioning mechanisms are used to distribute metadata among metadata servers. Sub-tree partition [27, 48, 50] is prone to load imbalance [46]. Full path indexing enables fine-grained load balancing [25, 35], but incurs multiple RPC lookup because permission checks must traverse the directory hierarchy step by step. Moreover, the lack of locality leads to high coordination overhead. To address these challenges, range partitioning [30, 43], which is also adopted by Mantle, is used to achieve load balance while mitigates distributed coordination. But our evaluation reveals this strategy still introduces significant coordination overhead in directory modification operations.

Path resolution. Client-side caching [21, 26, 38, 42] is used to minimize or eliminate the lookup RPCs. However, this approach is infeasible for COSSs. InfiniFS [26] speculatively uses parallel RPCs for fast lookup with poor scaling under high concurrency. FalconFS [52] lazily replicates all metadata to enable local lookup in any metadata server, but this approach is impractical in COSSs due to massive namespace sizes. CephFS [50] and FileScale [22] implement server-side caching atop subtree partitioning to improve lookup latency, yet they fall short of achieving the single-RPC lookup enabled by Mantle. Moreover, their approaches are prone to load imbalance and incur high migration overhead [46]. Duplex [10] caches path permissions on a central node, incurring high consistency overhead and falling back to parallel resolution after failures. In contrast, Mantle uses efficient data structures and lightweight indexing to ensure fast lookups, low maintenance overhead, and failure resilience.

Other works. Several studies propose replication protocols with high write throughput [12, 18, 34, 36, 53], offering opportunities to enhance directory modification performance in Mantle. Other works leverage emerging hardware, such as PM, RDMA, and SmartNICs, for high-performance metadata services [2, 15, 19, 23, 54], which are orthogonal to Mantle and can potentially complement its design.

9 Conclusion

Mantle offers a scalable solution for hierarchical metadata management for cloud object storage services, addressing challenges like high path resolution latency and directory modification contention. By utilizing IndexNode for single-RPC lookups, delta records, Raft-based replication, and balanced workload distribution, Mantle outperforms existing systems. Evaluations show its capability to handle billion-scale namespaces with high throughput and low latency, making it ideal for data-intensive cloud applications and future metadata services.

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