BlobSeer: How to Enable Efficient Versioning for Large Object Storage under Heavy Access Concurrency

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ABSTRACT

To accommodate the needs of large-scale distributed P2P systems, scalable data management strategies are required, allowing applications to efficiently cope with continuously growing, highly distributed data. This paper addresses the problem of efficiently storing and accessing very large binary data objects (blobs). It proposes an efficient versioning scheme allowing a large number of clients to concurrently *read, write and append* data to huge blobs that are fragmented and distributed at a very large scale. Scalability under heavy concurrency is achieved thanks to an original metadata scheme, based on a distributed segment tree built on top of a Distributed Hash Table (DHT). Our approach has been implemented and experimented within our *BlobSeer* prototype on the Grid'5000 testbed, using up to 175 nodes.

1. INTRODUCTION

Peer-to-peer (P2P) systems have extensively been studied during the last years as a means to achieve very large scale scalability for services and applications. This scalability is generally obtained through software architectures based on autonomic peers which may take part in a collaborative work process in a dynamic way: they may join or leave at any time, publish resources or use resources made available by other peers. P2P environments typically need scalable data management schemes able to cope with a growing number of clients and with a continuously growing data, (e.g. data streams), while supporting a dynamic and highly concurrent environment.

As the usage of the P2P approach extends to more and more application classes, the storage requirements for such a large scale are becoming increasingly complex due to the rate, scale and variety of data. In this context, storing, accessing and processing *very large, unstructured data* is of utmost importance. Unstructured data consists of free-form text such as word processing documents, e-mail, Web pages, text files, sources that contain natural language text, images, audio and video streams to name a few.

Studies show more than 80% [8] of data globally in circulation is unstructured. On the other hand, data sizes increase at a dramatic level: for example, medical experiments [15] have an average requirement of 1 TB per week. Large repositories for data analysis programs, data streams generated and updated by continuously running applications, data archives are just a few examples of contexts where unstructured data that easily reaches the order of 1 TB.

Unstructured data are often stored as a *binary large object (blob)* within a database or a file. However, these approaches can hardly cope with blobs which grow to huge sizes. To address this issue, specialized abstractions like MapReduce [5] and Pig-Latin [14] propose high-level data processing frameworks intended to hide the details of parallelization from the user. Such platforms are implemented on top of huge object storage and target high performance by optimizing the parallel execution of the computation. This leads to *heavy access concurrency* to the blobs, thus the need for the storage layer to offer support in this sense. Parallel and distributed file system also consider using objects for low-level storage [6, 17, 7]. In other scenarios, huge blobs need to be used concurrently at the highest level layers of applications directly: high-energy physics applications, multimedia processing [4] or astronomy [13].

In this paper we address the problem of storing and efficiently accessing very large unstructured data objects [11, 15] in a distributed environment. We focus on the case where data is *mutable* and potentially accessed by a very large number of concurrent, distributed processes, as it is typically the case in a P2P system. In this context, *versioning* is an important feature. Not only it allows to roll back data changes when desired, but it also enables cheap branching (possibly recursively): the same computation may proceed independently on different versions of the blob. Versioning should obviously not significantly impact access performance to the object, given that objects are under constant heavy access concurrency. On the other hand, versioning leads to increased storage space usage and becomes a major concern when the data size itself is huge. Versioning efficiency thus refers to both access performance under heavy load and reasonably acceptable overhead of storage space.

Related work has been carried out in the area of parallel and distributed file systems [1, 3, 7] and archiving systems [18]: in all these systems the metadata management is centralized and mainly optimized for data reading and appending. In contrast, we rely on metadata decentralization, in order to introduce an *efficient versioning* scheme for huge, large-scale distributed blobs that are concurrently accessed by an arbitrarily large number of clients which may read, write or append data to blobs. Our algorithm guarantees atomicity while still attaining good data access performance. Our approach splits a huge blob into small fixed-sized pages that are scattered across commodity data providers. Rather than updat-

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ing the current pages, completely new pages are generated when clients request data modifications. The corresponding metadata is "weaved" with old metadata in such way as to offer a complete virtual view of both the past version and the current version of the blob. Metadata is organized as a segment-tree like structure (see Section 4) and is also scattered across the system using a Distributed Hash Table (DHT). Distributing data and metadata not only enables high performance through parallel, direct access I/O paths, but also favors efficient use of storage space: although a full virtual view of all past versions of the blob is offered, real space is consumed only by the newly generated pages.

Our approach has been implemented and experimented within our prototype, called *BlobSeer*: a binary large object management service. In previous work [13, 12] we have handled versioning in a static way: blobs were considered huge storage objects of predefined, *fixed* sizes that are first allocated, then manipulated by reading and writing parts of them. However, in most real life scenarios, blobs need to dynamically grow, as new data is continuously gathered. This paper improves on our previous work as follows. First, we introduce support for dynamic blob expansion through atomic append operations. Second, we introduce cheap branching, allowing a blob to evolve in multiple, completely different ways through writes and appends starting from a particular snapshot version. This may be very useful for exploring alternative data processing algorithms starting from the same blob version.

The paper is organized as follows. Section 2 restates the specification of the problem in a more formal way. Section 3 provides an overview of our design and precisely describes how data access operations are handled. The algorithms used for metadata management are discussed in Section 4. Section 5 provides a few implementation details and reports on the experimental evaluation performed on multi-site grid testbed. On-going and future work is discussed in Section 6.

2. SPECIFICATION

Our goal is to enable efficient versioning of blobs in a highly concurrent environment. In such a context, an arbitrarily large number of n clients compete to read and update the blob. A blob grows as clients append new data and its contents may be modified by partial or total overwriting.

Each time the blob gets updated, a new snapshot reflecting the changes and labeled with an incremental version is generated, rather than overwriting any existing data. This allows access to all past versions of the blob. In its initial state, we assume any blob is considered empty (its size is 0) and is labeled with version 0.(Note that our previous work [13, 12] was relying on different assumptions: the blob size was statically specified at the initialization time and could not be extended.)

Updates are totally ordered: if a snapshot is labeled by version k, then its content reflects the successive application of all updates $1..k-1$ on the initial empty snapshot in this order. Thus generating a new snapshot labeled with version k is semantically equivalent to applying the update to a copy of the snapshot labeled with version $k-1$. As a convention, we will refer to the snapshot labeled with version k simply by *snapshot* k from now on.

2.1 Interface

To create a new blob, one must call the CREATE primitive:

id = CREATE( )

This primitive creates the blob and associates to it an empty snapshot 0. The blob will be identified by its id (the returned value). The *id* is guaranteed to be globally unique.

vw = WRITE(id, buffer, offset , size)

A WRITE initiates the process of generating a new snapshot of the blob (identified by id) by replacing *size* bytes of the blob starting at *offset* with the contents of the local *buffer*.

The WRITE does not know in advance which snapshot version it will generate, as the updates are totally ordered and internally managed by the storage system. However, after the primitive returns, the caller learns about its assigned snapshot version by consulting the returned value vw. The update will eventually be applied to the snapshot $vw-1$, thus effectively generating the snapshot vw. This snapshot version is said to be *published* when it becomes available to the readers. Note that the primitive may return before snapshot version vw is published. The publication time is unknown, but the WRITE is *atomic* in the sense of [9]: it appears to execute instantaneously at some point between its invocation and completion. Completion in our context refers to the moment in time when the newly generated snapshot vw is published.

Finally, note that the WRITE primitive fails if the specified *offset* is larger than the total size of the snapshot $vw-1$.

va = APPEND(id, buffer, size)

APPEND is a special case of WRITE, in which the *offset* is implicitly assumed to be the size of snapshot $va-1$.

READ(id, v, buffer , offset , size)

A READ results in replacing the contents of the local *buffer* with *size* bytes from the snapshot version v of the blob id, starting at *offset*, if v has already been published. If *v* has not yet been published, the read fails. A read fails also if the total size of the snapshot *v* is smaller than *offset + size*.

Note that the caller of the READ primitive must be able to learn about the new versions that are published in the system in order to provide a meaningful value for the v argument. The blob size corresponding to snapshot v is also required, to enable valid s from the blob to be read. The following primitives are therefore provided:

v = GET_RECENT(id)

This primitive returns a recently published version blob id. The system guarantees that $v \geq max(v_k)$, for all snapshot versions v_k published before the call.

size = GET_SIZE(id, v)

This primitive returns the size of the blob snapshot corresponding to version *v* of the blob identified by id. The primitive fails if v has not been published yet.

Since WRITE and APPEND may return before the corresponding snapshot version is published, a subsequent READ attempted by the same client on the very same snapshot version may fail. However, it is desirable to be able to provide support for "read your writes" consistency. For this purpose, the following primitive is added:

SYNC(id, v)

The caller of SYNC blocks until snapshot v of blob id is published.

Our system also introduces support for branching, to allow alternative evolutions of the blob through WRITE and APPEND starting from a specified version.

bid = BRANCH(id, v)

This primitive virtually duplicates the blob identified by id by creating a new blob identified by bid. This new blob is identical to the original blob in every snapshot up to (and including) v. The first WRITE or APPEND on the blob bid will generate a new snapshot $v + 1$ for blob bid. The primitive fails if version v of the blob identified by id has not been published yet.

2.2 Usage scenario

Let us consider a simple motivating scenario illustrating the use of our proposed interface. A digital processing company offers online picture enhancing services for a wide user audience. Users upload their picture, select a desired filter, such as sharpen and download their picture back. Most pictures taken with a modern camera include some metadata in their header, describing attributes like camera type, shutter speed, ambient light levels, etc. Thousands of users upload pictures every day, and the company would like to analyze these pictures for statistical purposes. For example it might be interesting to find out the average contrast quality for each camera type.

One option to address this problem would be to store the pictures in a huge database and perform some query when needed. Unfortunately, pictures are unstructured data: metadata is not standardized and may differ from one camera brand to another. Thus, no consistent schema can be designed for query optimization. Moreover, it is unfeasible to store variable binary data in a database, because database systems are usually fine-tuned for fixed-sized records.

Let us now consider using a virtually unique (but physically distributed) blob for the whole dataset. Pictures are APPEND'ed concurrently to the blob from multiple sites serving the users, while a recent version of the blob is processed at regular intervals: a set of workers READ disjoint parts of the blob, identify the set of pictures contained in their assigned part, extract from each picture the camera type and compute a contrast quality coefficient, and finally aggregate the contrast quality for each camera type. This type of computation fits in the class of map-reduce applications. The map phase generates a set of (key, value) pairs from the blob, while the reduce phase computes some aggregation function over all values corresponding to the same key. In our example the keys correspond to camera types.

Many times during a map phase it may be necessary to overwrite parts of the blob. For example, a complex image processing was necessary for some pictures and overwriting the picture with its processed version saves computation time when processing future blob versions. Surely, a map with an idempotent reduce reaches the same result with no need to write, but at the cost of creating an output that duplicates the blob, which means an unacceptable loss of storage space.

3. DESIGN OVERVIEW

Our system is striping-based: a blob is made up of blocks of a fixed size *psize*, referred to as *pages*. Each page is assigned to a fixed range of the blob $(k \times psize, (k+1) \times psize - 1)$. Any range that covers a full number of pages is said to be *aligned*. These pages are distributed among storage space providers. *Metadata* facilitates access to a range *(offset, size)* for any existing version of a blob snapshot, by associating such a range with the page providers.

A WRITE or APPEND generates a *new* set of pages corresponding to the offset and size requested to be updated. Metadata is then generated and "weaved" together with the old metadata in such way as to create the illusion of a new incremental snapshot that actually shares the unmodified pages with the older versions. Thus, two successive snapshots v and $v+1$ physically share the pages that fall outside of the range of the update that generated snapshot $v + 1$.

Consider a read for snapshot v whose range fits exactly a single page. The physical page that is accessed was produced by some update that generated snapshot w, with $w \leq v$ such that w is the highest snapshot version generated by an update whose range intersects the page. Therefore, when the range of a READ covers several pages, these pages may have been generated by different updates. Updates that do not cover full pages are handled in a slightly more complex way, but not discussed here, due to space constraints.

3.1 Architecture overview

Our distributed service consists of communicating processes, each fulfilling a particular role.

Clients may create blobs and read, write and append data to them. There may be multiple concurrent clients, and their number may dynamically vary in time.

Data providers physically store the pages generated by WRITE and APPEND. New data providers may dynamically join and leave the system.

The provider manager keeps information about the available storage space. Each joining provider registers with the provider manager. The provider manager decides which providers should be used to store the generated pages according to a strategy aiming at ensuring an even distribution of pages among providers.

The metadata provider physically stores the metadata allowing clients to find the pages corresponding to the blob snapshot version. Note that the metadata provider may be implemented in a distributed way. However, for the sake of readability, we do not develop this aspect in our presentation of the algorithms we propose for data access. Distributed metadata management is addressed in detail in Section 4.

The version manager is the key actor of the system. It registers update requests (APPEND and WRITE), assigning snapshot version numbers, end eventually publishes these updates, guaranteeing total ordering and atomicity.

Our design targets scalability and large-scale distribution. Therefore, we make a key design choice in avoiding a static role distribution: any physical node may play one or multiple roles, as a client, or by hosting data or metadata. This scheme makes our system suitable for a P2P environment.

3.2 Reading data

The READ primitive is presented in Algorithm 1. The client contacts the version manager first, to check whether the supplied version *v* has been published and fails if it is not the case. Otherwise, the client needs find out what pages fully cover the requested *offset* and *size* for version *v* and where they are stored. To this purpose, the client contacts the metadata provider and receives the required metadata. Then it processes the metadata to generate a set of page descriptors PD. PD holds information about all pages that need to be fetched: for each page its globally unique page id pid, its index i in the buffer to be read and the page $provider$ that stores it. (Note that, for the sake of simplicity, we consider here the case where each page is stored on a single provider. Replication strategies will be investigated in future work.) Having this information assembled, the client fetches the pages in parallel and fills the local *buffer*. Note that the range defined by the supplied *offset* and $size$ may not be aligned to full pages. In this case the client may request only a part of the page from the page provider.

Algorithm 1 READ

Require: The snapshot version v
Require: The local *buffer* to read to
Require: The *offset* in the blob
Require: The *size* to read
1: **if** v is not published **then**
2: **fail**
3: **end if**
4: $PD \leftarrow$ *READ_METADATA(v, offset, size)*
5: **for all** $(pid, i, provider) \in PD$ **in parallel do**
6: read pid from $provider$ into $buffer$ at $i \times psize$
7: **end for**
8: **return success**

Note that, at this stage, for readability reasons, we have not developed yet the details of metadata management. However, the key mechanism that enables powerful properties such as efficient fine-grain access under heavy concurrency relates directly to metadata management, as discussed in Section 4.

3.3 Writing and appending data

Algorithm 2 describes how the WRITE primitive works. For simplicity, we first consider here aligned writes only, with page size *psize*. Unaligned writes are also handled by our system, but, due to space constraints, this case is not discussed here. The client first needs to determine the number of pages n that cover the range. Then, it contacts the provider manager requesting a list of n page providers PP (one for each page) that are capable of storing the pages. For each page in parallel, the client generates a globally unique page id pid, contacts the corresponding page provider and stores the contents of the page on it. It then updates the set of page descriptors PD accordingly. This set is later used to build the metadata associated with this update. After successful completion of this stage, the client contacts the version manager and registers its update. The version manager assigns to this update a new snapshot version vw and communicates it to the client, which then generates new metadata and "weaves" (details in section 4) it together with the old metadata such that the new snapshot vw appears as a standalone entity. Finally it notifies the version manager of success, and returns successfully to the user. At this point, the version manager takes the responsibility of eventually publishing vw.

APPEND is almost identical to the WRITE, with the difference that an *offset* is directly provided by the version manager at the time when snapshot version is assigned. This offset is the size of the previously published snapshot version.

Algorithm 2 WRITE

Require: The local *buffer* used to apply the update.
Require: The *offset* in the blob.
Require: The *size* to write.
Ensure: The assigned version vw to be published.
1: $n \leftarrow (offset + size)/psize$
2: $PP \leftarrow$ the list of n page providers
3: $PD \leftarrow \emptyset$
4: **for all** $0 \leq i < n$ **in parallel do**
5: $pid \leftarrow$ unique page id
6: $provider \leftarrow PP[i]$
7: store page pid from $buffer$ at $i \times psize$ to $provider$
8: $PD \leftarrow PD \cup (pid, i, provider)$
9: **end for**
10: $vw \leftarrow$ assigned snapshot version
11: *BUILD_METADATA(vw, offset, size, PD)*
12: notify version manager of success
13: **return** vw

Note that our algorithm enables a high degree of parallelism: for any update (WRITE or APPEND), pages may be asynchronously sent and stored in parallel on providers. Moreover, multiple clients may perform such operations with full parallelism: no synchronization is needed for writing the data, since each update generates new pages. Some synchronization is necessary when writing the *metadata*, however the induced overhead is low (see Section 4).

4. METADATA MANAGEMENT

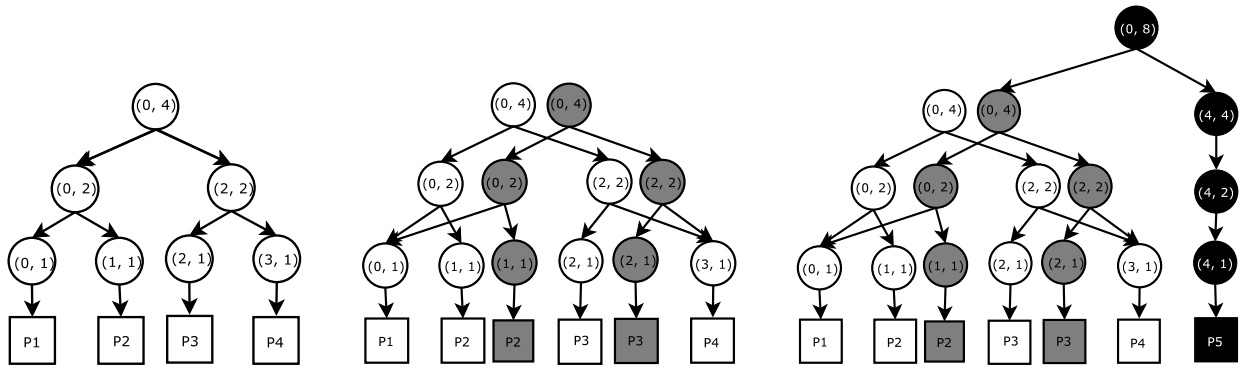
Metadata stores information about the pages which make up a given blob, for each generated snapshot version. We choose a simple, yet versatile design, allowing the system to efficiently build a full view of the new snapshot of the blob each time an update occurs. This is made possible through a key design choice: when updating data, new metadata is created, rather than updating old metadata. As we will explain below, this decision significantly helps us provide support for heavy concurrency, as it favors *independent concurrent accesses to metadata without synchronization*.

4.1 The distributed metadata tree

We organize metadata as a *distributed segment tree* [19], one associated to each snapshot version of a given blob id. A segment tree is a binary tree in which each node is associated to a range of the blob, delimited by *offset* and *size*. We say that the node *covers* the range (*offset*, *size*). For each node that is not a leaf, the left child covers the first half of the range, and the right child covers the second half. Each leaf covers a single page. We assume the page size $psize$ is a power of two.

For example, Figure 1(a) depicts the structure of the metadata for a blob consisting of four pages. We assume the page size is 1. The root of the tree covers the range $(0, 4)$ (i.e., *offset* = 0, *size* = 4 pages), while each leaf covers exactly one page in this range.

Tree nodes are stored on the metadata provider in a distributed way, using a simple DHT (Distributed Hash Table). This choice favors concurrent access to metadata, as explained in Section 4.2. Each tree node is identified uniquely by its version and range specified by the offset and size it covers. Inner nodes hold the version of the



(a) The metadata after a write of four pages

(b) The metadata after overwriting two pages

(c) The metadata after an append of one page

Figure 1: Metadata representation

left child vl and the version of the right child vr, while leaves hold the page id pid and the $provider$ that store the page.

Sharing metadata across snapshot versions. Such a metadata tree is created when the first pages of the blob are written, for the range covered by those pages. Note that rebuilding a *full* tree for subsequent updates would be space- and time-inefficient. This can be avoided by *sharing* the existing tree nodes that cover the blob ranges which do *not* intersect with the range of the update to be processed. Of course, new tree nodes are created for the ranges that *do* intersect with the range of the update. These new tree nodes are "weaved" with existing tree nodes generated by past updates, in order to build a a new consistent view of the blob, corresponding to a new snapshot version. This process is illustrated on Figures 1(a) and 1(b). Figure 1(a) corresponds to an initial snapshot version (1) of a 4-page blob, whereas Figure 1(b) illustrates how metadata evolves when pages 2 and 3 of this blob are modified (snapshot version 2). Versions are color-coded: the initial snapshot 1 is white, snapshot 2 is grey. When a WRITE updates the second and third page of the blob, the grey nodes are generated: $(1, 1)$, $(2, 1)$, $(0, 2)$, $(2, 2)$, $(0, 4)$. These new grey nodes are "weaved" with existing white nodes corresponding to the unmodified pages 1 and 4. Therefore, the left child of the grey node that covers $(0, 2)$ is the white node that covers $(0, 1)$; similarly, the right child of the grey node that covers $(2, 2)$ is the white node covering $(3, 1)$.

Expanding the metadata tree. APPEND operations make the blob "grow": consequently, the metadata tree gets expanded, as illustrated on Figure 1(c). Continuing our example, we assume that the WRITE generating snapshot version 2 is followed by an APPEND for one page, which generates snapshot version 3 of the blob (black-colored). New metadata tree nodes are generated, to take into account the creation of the fifth page. The left child of the new black root,$(0, 8)$ is the old, grey root of snapshot 2, $(0, 4)$.

4.2 Accessing metadata: algorithms

Reading metadata. During a READ, the metadata is accessed (Algorithm 3) in order to find out what pages fully cover the requested range R delimited by *offset* and $size$. It is therefore necessary to traverse down the segment tree, starting from the root that corresponds to the requested snapshot version. A node N that covers segment R_N is explored if the intersection of R_N with R is not empty. All explored leaves reached this way are used to build the set of page descriptors PD that is used to fetch the contents of the pages. To simplify the presentation of the algorithm, we introduce two primitives. $GET\_NODE(v, offset, size)$ fetches and returns the contents of the node identified by the supplied version, offset and size from the metadata provider. Similarly, $GET\_ROOT(v)$ fetches and returns the root of the tree corresponding to version v.

Algorithm 3 $READ\_META$

Require: The snapshot version v
Require: The $offset$ of the blob
Require: The $size$ to read
Ensure: The set of page descriptors PD
1: $NS \leftarrow \{GET\_ROOT(v)\}$
2: **while** $NS \neq \emptyset$ **do**
3: $N \leftarrow$ extract node from NS
4: **if** N is leaf **then**
5: $i \leftarrow (N.offset - offset)/psize$
6: $PD \leftarrow PD \cup (N.pid, i, N.provider)$
7: **else**
8: **if** $(offset, size)$ intersects $(N.offset, N.size/2)$ **then**
9: $NS \leftarrow NS \cup GET\_NODE(N.vl, N.offset, N.size/2)$
10: **end if**
11: **if** $(offset, size)$ intersects $(N.offset + N.size/2, N.size/2)$ **then**
12: $NS \leftarrow NS \cup GET\_NODE(N.vr, N.offset + N.size/2, N.size/2)$
13: **end if**
14: **end if**
15: **end while**

Writing metadata. For each update (WRITE or APPEND) producing snapshot version *vw*, it is necessary to build a new metadata tree (possibly sharing nodes with the trees corresponding to previous snapshot versions). This new tree is the smallest (possibly incomplete) binary tree such that its leaves are exactly the leaves covering the pages of range that is written. The tree is built bottom-up: first the leaves corresponding to the newly generated pages are built, then the inner nodes P are built up to (and including) the root. This process is illustrated in Algorithm 4. Note that inner nodes

may have children which do *not* intersect the range of the update to be processed. For any given snapshot version vw, these nodes form the *set of border nodes* B_{vw}. When building the metadata tree, the algorithm needs to compute the corresponding versions of such children nodes (vl or vr). For simplicity, we do not develop here how the set of border nodes is computed before building the tree.

Algorithm 4 $BUILD\_META$

Require: The assigned snapshot version vw.
Require: The $offset$ in the blob.
Require: The $size$ to write.
Require: The set of page descriptors PD.
Ensure:
1: $Q \leftarrow \emptyset$
2: $B_{vw} \leftarrow$ build the set of border nodes
3: **for all** $(pid, i, provider) \in PD$ **do**
4: $N \leftarrow NEW\_NODE(vw, offset + i \times psize, psize)$
5: $N.pid \leftarrow pid$
6: $N.provider \leftarrow provider$
7: $Q \leftarrow Q \cup \{N\}$
8: **end for**
9: $V \leftarrow Q$
10: **while** $Q \neq \emptyset$ **do**
11: $N \leftarrow$ extract a node from Q
12: **if** N is not root **then**
13: **if** $N.offset\%(2 \times N.size) = 0$ **then**
14: $P \leftarrow NEW\_NODE(vw, N.offset, 2 \times N.size)$
15: $position \leftarrow LEFT$
16: **else**
17: $P \leftarrow NEW\_NODE(vw, N.offset - N.size, 2 \times N.size)$
18: $position \leftarrow RIGHT$
19: **end if**
20: **if** P not $\in V$ **then**
21: **if** $position = LEFT$ **then**
22: $P.vl \leftarrow vw$
23: $P.vr \leftarrow$ extract right child version from B_{vw}
24: **end if**
25: **if** $position = RIGHT$ **then**
26: $P.vr \leftarrow vw$
27: $P.vl \leftarrow$ extract left child version from B_{vw}
28: **end if**
29: $Q \leftarrow Q \cup \{P\}$
30: $V \leftarrow V \cup \{P\}$
31: **end if**
32: **end if**
33: **end while**
34: **for all** $N \in V$ **in parallel do**
35: write N to the metadata provider
36: **end for**

Why WRITEs and APPENDs may proceed in parallel. Building new metadata tree nodes might seem to require serialization. Consider two concurrent clients C_1 and C_2. Let us assume that, after having written their pages in parallel, with no synchronization, that contact the version manager to get their snapshot versions. Let us assume C_1 gets snapshot versions vw and C_2 gets snapshot version $vw + 1$. The two clients should then start to build their metadata tree nodes concurrently. However, it may seem that client C_2 must wait for client C_1 to complete writing metadata, because tree nodes built by C_1 may actually be part of the set of border nodes of C_2, which is used by C_2 to build its own tree nodes.

As our goal is to favor concurrent WRITEs and APPENDs (and, consequently, concurrent metadata writing), we choose to avoid such a serialization by introducing a small computation overhead. Note that C_2 may easily compute the border node set B_2 by descending the tree (starting from the root) corresponding to snapshot vw generated by C_1. It may thus gather all left and right children of the nodes which intersect the range of the update corresponding to snapshot $vw + 1$. If the root of snapshot $vw + 1$ covers a larger range than the root of snapshot vw, then the set of border nodes contains exactly one node: the root of snapshot vw. Our main difficulty comes from the nodes that are build by C_1 that can actually be part of set of border nodes of C_2, because all other nodes of the set of border nodes of C_2 can be computed as described above, by using the root of the latest published snapshot vp instead of the root of vw.

Our solution to this is to introduce a small computation overhead in the version manager, who will supply the problematic tree nodes that are part of the set of border nodes directly to the writer at the moment it is assigned a new snapshot version. This is possible because the range of each concurrent WRITE or APPEND is registered by the version manager. Such operations are considered said to be *concurrent* with the update being processed if they have been assigned a version number (after writing their data), but they have not been published yet (e.g. because they have not finished writing the corresponding metadata). By iterating through the concurrent WRITE and APPEND operations (which have been assigned a lower snapshot version), the version manager will build the partial set of border nodes and provide it to the writer when it asks for the snapshot version. The version manager also supplies a recently published snapshot version that can be used by the writer to compute the rest of the border nodes. Armed with both the partial set of border nodes and a published snapshot version, the writer is now able to compute the full set of border nodes with respect to the supplied snapshot version.

4.3 Discussion

Our approach enables efficient versioning both in terms of performance under heavy load and in terms of required storage space. Below we discuss some of the properties of our system.

Support for heavy access concurrency. Given that updates always generate new pages instead of overwriting older pages, READ, WRITE and APPEND primitives called by concurrent clients may fully proceed in parallel at the application-level, with no need for explicit synchronization. This is a key feature of our distributed algorithm. Internally, synchronization is kept minimal: distinct pages may read or updated in a fully parallel way; data access serialization is only necessary when the same provider is contacted at the same time by different clients, either for reading or for writing. It is important to note that the strategy employed by the provider manager for page-to-provider distribution plays a central role in minimizing such conflicts that lead to serialization.

Note on the other hand that internal serialization is necessary when two updates (WRITE or APPEND) contact the version manager simultaneously to obtain a snapshot version. This step is hoverer negligible when compared to the full operation.

Finally, the scheme we use for metadata management also aims

at enabling parallel access to metadata as much as possible. The situations where synchronization is necessary have been discussed in Section 4.2.

Efficient use of storage space. Note that new storage space is necessary for newly written pages only: for any WRITE or APPEND, the pages that are NOT updated are physically shared by the newly generated snapshot version with the previously published version. This way, the same physical page may be shared by a large number of snapshot versions of the same blob. Moreover, as explained in Section 4, multiple snapshot versions may partially share metadata.

Atomicity. Recent arguments [9, 10, 16] stress the need to provide *atomicity* for operations on objects. An atomic storage algorithm must guarantee any read or write operation appears to execute instantaneously between its invocation and completion despite concurrent access from any number of clients. In our architecture, the version manager is responsible for assigning snapshot versions and for publishing them upon successful completion of WRITEs and APPENDs. Note that concurrent WRITEs and APPENDs work in complete isolation, as they do not *modify*, but rather *add* data and metadata. It is then up the the version manager to decide when their effects will be revealed to the other clients, by publishing their assigned versions in a consistent way. The only synchronization occurs at the level at the version manager. In our current implementation, atomicity is easy to achieve, as the version manager is centralized. Using a distributed version manager will be addressed in the near future.

5. EXPERIMENTAL EVALUATION

We experimented and evaluated the approach developed above within the framework of our BlobSeer prototype. To implement the metadata provider in a distributed way, we have developed a custom DHT (Distributed Hash Table), based on simple static distribution scheme. This allows metadata to be efficiently stored and retrieved in parallel.

Evaluations have been performed on the Grid'5000 [2] testbed, an experimental Grid platform gathering 9 sites geographically distributed in France. In each experiment, we used at most 175 nodes of the Rennes site of Grid'5000. Nodes are outfitted with x86_64 CPUs and 4 GB of RAM. Intracluster bandwidth is 1 Gbit/s (measured: 117.5MB/s for TCP sockets with MTU = 1500 B), latency is 0.1 ms.

We first ran a set of experiments to evaluate the impact of our metadata scheme over the performance of the APPEND operation (in terms of bandwidth), while the blob size continuously grows. In these experiments, a single client process creates an empty blob and starts appending to it, while we constantly monitor the bandwidth of the APPEND operation.

We use two deployment settings. We deploy each the version manager and the provider manager on two distinct dedicated nodes, and we co-deploy a data provider and a metadata provider on the other nodes, using a total of 50 data and metadata providers in the first setting and 175 data and metadata providers in the second setting. In each of the two settings, a client creates a blob and starts appending 64 MB of data to the blob. This process is repeated two times, using a different page size each time: 64 KB and 256 KB.

Results are shown in Figure 2(a): they show that a high bandwidth is maintained even when the blob grows to large sizes, thus demonstrating a low metadata overhead. A slight bandwidth decrease is observed when the number of pages reaches a power of two: this corresponds to the expected metadata overhead increase caused by adding a new level to the metadata tree.

A second set of experiments evaluates the bandwidth performance when multiple readers access disjoint parts of the same blob. We use again 175 nodes for these experiments. As in the previous case, the version manager and the provider manager are deployed on two dedicated nodes, while a data provider and a metadata provider are co-deployed on the remaining 173 nodes.

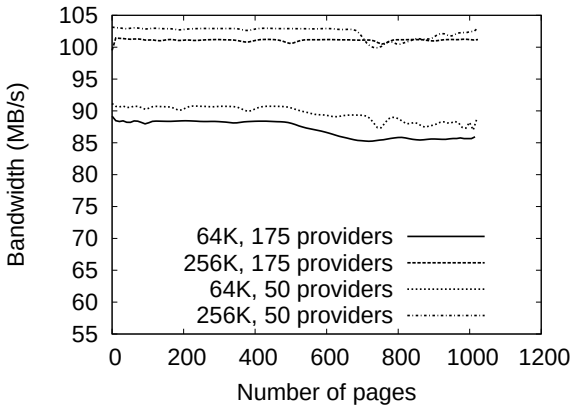
In a first phase, a single client appends data to the blob until the blob grows to 64 GB. Then, we start reading the first 64 MB from the blob with a single client. This process is repeated 100 times and the average bandwidth computed. Then, we increase the number of readers to 100. The readers are deployed on nodes that already run a data and metadata provider. They concurrently read distinct 64 MB chunks from the blob. Again, the process in repeated 100 times, and the average read bandwidth is computed. In a last step the number of concurrent clients is increased to 175 and the same process repeated, obtaining another average read bandwidth.

Note that, even there is no conflict for accessing the same data, the readers concurrently traverse the metadata tree, whose nodes may be concurrently requested by multiple readers. Note also that, as the number of pages of the blob is very large with respect to the total number of available metadata and data providers, each physical node may be subject to heavily concurrent requests.

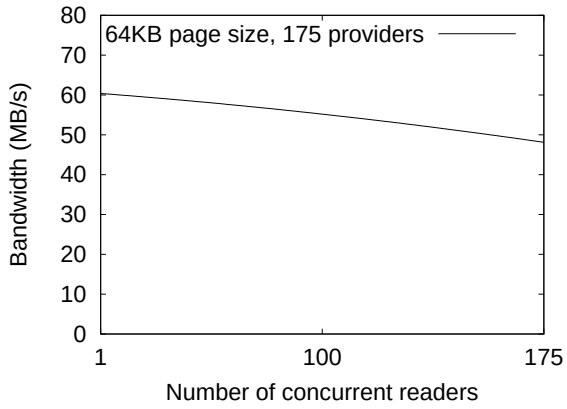
The obtained results are represented in Figure 2(b), where the average read bandwidth is represented as a function of the number of concurrent readers, interpolated to fit the three experiments. We observe a very good scalability: the read bandwidth drops from 60MB/s for a single reader to 49MB/s for 175 concurrent readers.

6. CONCLUSION

As more and more application classes and services start using the P2P paradigm in order to achieve high scalability, the demand for adequate, scalable data management strategies is ever higher. One important requirement in this context is the ability to efficiently cope with accesses to continuously growing data, while supporting a highly concurrent, highly distributed environment. We address this requirement for the case of huge *unstructured* data. We propose an efficient versioning scheme allowing a large number of clients to concurrently *read, write and append* data to binary large objects (blobs) that are fragmented and distributed at a very large scale. Our algorithms guarantees atomicity while still achieving a good data access performance. To favor scalability under heavy concurrency, we rely on an original metadata scheme, based on a distributed segment tree that we build on top of a Distributed Hash Table (DHT). Rather than modifying data and metadata in place when data updates are requested, new data fragments are created, and the corresponding metadata are "weaved" with the old metadata, in order to provide a new view of the whole blob, in a space-efficient way. This approach favors independent, concurrent accesses to data and metadata without synchronization and thereby enables a high throughput under heavy concurrency. The proposed algorithms have been implemented within our *BlobSeer* prototype and experimented on the Grid'5000 testbed, using up to 175 nodes: the preliminary results suggest a good scalability with respect to the



(a) Append throughput as a blob dynamically grows



(b) Read throughput under concurrency

Figure 2: Experimental results: data throughput

data size and to the number of concurrent accesses. Further experimentations are in progress, which aim at demonstrating the benefits of data and metadata distribution. We also intend to investigate extensions to our approach allowing to add support for volatility and failures.

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