Scalable, Structured Data Placement over P2P Storage Utilities

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Current peer-to-peer storage utilities offer a convenient flat storage space, delegating the organization and presentation of data to upper layers. In reality, both applications and users typically organize data in a structured form. One such popular structure is hierarchical namespace as employed in a file system. A naive approach such as hashing the pathname of file system not only ignores locality in important operations such as file/directory lookup, but also results in uncontrollable, massive object relocations when rename on path component occurs.

In this paper, we investigate policies and strategies that map the hierarchical namespace onto the flat storage space of P2P systems. We found that, in general, there exists a tradeoff between lookup performance and balanced storage utilization, and attempts to balance these two requirements calls for intelligent placement decision. We show that simple heuristics are effective in achieving significant performance benefit with negligible overhead. In addition, combining some of the heuristics and carefully setting the parameters can significantly reduce the lookup cost while keeping the impact on storage utilization minimal. These algorithms are robust and generic, capable of handling data layout to capture access locality.

[1] Microsoft Research Asia. This work was done while Zhang was at Hewlett-Packard Laboratories

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Abstract

Current peer-to-peer storage utilities offer a convenient flat storage space, delegating the organization and presentation of data to upper layers. In reality, both applications and users typically organize data in a structured form. One such popular structure is hierarchical namespace as employed in a file system. A naïve approach such as hashing the pathname of file system not only ignores locality in important operations such as file/directory lookup, but also results in uncontrollable, massive object relocations when rename on path component occurs.

In this paper, we investigate policies and strategies that map the hierarchical namespace onto the flat storage space of P2P systems. We found that, in general, there exists a tradeoff between lookup performance and balanced storage utilization, and attempts to balance these two requirements calls for intelligent placement decision. We show that simple heuristics are effective in achieving significant performance benefit with negligible overhead. In addition, combining some of the heuristics and carefully setting the parameters can significantly reduce the lookup cost while keeping the impact on storage utilization minimal. These algorithms are robust and generic, capable of handling data layout to capture access locality.

1 Introduction

With the rapid growth of the Internet and ever-rising demand of the application, building a highly scalable infrastructure is becoming increasingly important. Such an infrastructure should be self-managed, decentralized, and capable of adapting automatically to the varying system conditions. For many, this happens to be the characteristics of Peer-to-Peer (P2P) networks [1] [2] [3] [4].

An infrastructure must provide various core services. One of such core services is information search and retrieval. To this end, there are several options. For example, in Gnutella [5], each individual node hosts a number of objects over which local index is built. Locating an object thus becomes the problem of distributed indexing and searching. While this is adequate for content sharing, such approaches lack the performance efficiency and hard guarantees demanded by certain applications. This lack of hard guarantee is addressed by some of the recent P2P systems [3, 4, 6]. These systems offer an administration-free and fault-tolerant storage utility. Nodes in these systems collectively contribute towards a storage space, in a self-organizing fashion. Unfortunately, these P2P storage architectures do not offer support for structuring data, other than assuming a distributed hash table.

One of the most dominant options for structuring data is a hierarchical namespace. The importance of a hierarchical namespace should not be overlooked. When such a facility is available, searching can be done more efficiently: locating an object is reduced to a lookup operation to the object's parent directory. Indeed, both applications and ordinary users have the intuitive notion of organizing information into a tree-like hierarchical namespace. Furthermore, a namespace is certainly what many (if not all) legacy applications expect. We believe that applications such as rich content distribution and interaction can benefit from structuring data (e.g., a tree) to describe the relationship amongst the participating nodes.

As a result, the imminent gap between structured data required by upper level applications and the flat storage abstraction offered by P2P networks underneath must be bridged. Policies and strategies to map the structured data onto the flat storage space of P2P systems is the focus of this study.

We choose to investigate hierarchical namespace for metadata placement, since this type of distributed data structure is the most distant from the flat nature of P2P storage space, and is important for many applications.

Our approach is pragmatic in that the placement decision is application-driven, by accounting for the locality exhibited in those most frequent operations. However, locality should not be the only consideration. The time taken to make intelligent choices, the robustness against various shapes of tree and the order in which the tree is constructed, and most importantly the ability to preserve the uniform storage utilization in large scale, must be respected as well. The end results are mechanisms achieving a careful balance among all these factors. In contrast, current proposals support distributing objects randomly *anywhere* over the flat storage space. While simple to implement and yielding good storage utilization overall, these approaches neglect the performance aspect. Furthermore, as we will argue later, a straightforward implementation by hashing pathname to place objects randomly will result in uncontrollable and massive object relocation when structural changing operations such as rename occur.

Such pragmatic approach requires high frequent operations be first identified. In traditional file system studies, it has been shown that lookup requests comprise a surprisingly high portion of total metadata operations [7]. Moving towards large-scale deployment, we envision this pattern to continue. As a matter of fact, NSFv4 [8] explicitly tries to address this issue by providing multi-component lookup. Optimizing lookups maybe even more important in distributed file systems using P2P overlay, since operations such as create is proceeded by a lookup to the parent directory, after that the actual creation can bypass normal routing infrastructure and operate on the parent object directly.

To summarize, the overarching design requirements are:

- **Performance**: high frequency operations such as lookup must be delivered with great efficiency. In addition, the time to decide where to place an object, given all other constraints, should also be reasonable.
- **Resource balance**: The purpose of efficient resource (e.g. storage) utilization in large scale peer-to-peer network is important, since bad resource utilization may create "hot spots" and system imbalance that can degrade performance.
- **Robustness**: tree shape and construction order should have a negligible impact to both performance and resource balance.

This paper reports our early investigation into this issue. We found that, in general, there exists a tradeoff between lookup performance and uniform resource utilization, and attempts to balance these two requirements require intelligent placement decision that may incur some additional overhead. We show that simple heuristics are effective in meeting these goals. The three algorithms we proposed, *radius-delta*, *hill-climbing* and *zoom-in*, can easily cut down more than half of the lookup costs from the naïve random placement approach. Some of the algorithms even have better resource utilization than the pure random policy. They are also robust to tree shapes and construction order. Our current investigation focuses on CAN as the chosen overlay platform and file system as way to structure data. While these algorithms are primarily designed for metadata placement, we believe they are generic enough to handle layout for data objects, where sequential access and pre-fetching exhibits similar locality behavior.

The rest of the paper is organized as follows. Section 2 gives the background of the study, which includes a short overview of P2P and CAN, and details of various options for constructing a hierarchical namespace and conducting a lookup procedure. We then discuss the three approaches for lookup optimizations in Section 3. Detailed evaluation and analysis are offered in Section 4. Section 5 discusses a few orthogonal optimizations. Related works are covered in Section 6 and we conclude in Section 7.

2 Background

2.1 Overview of P2P systems and CAN

The peer-to-peer systems we are interested in are those that will guarantee the retrieval of an existing object, as opposed to systems such as Freenet [9]. Important flavors of such systems include CAN [4], Pastry [2], Tapestry [1] and Chord [3]. All of these systems can be regarded as a distributed hash: lookup an object is equivalent to searching with the key associated with the object. Similarly, the concept of hashing bucket is mapped to a node in the system. Consequently, object query becomes routing in the overlay network composed by the participating nodes (buckets in the hash). The performance of a query is the product of number of routing hops taken in the overlay network (we call them *logical* hops) and the latency per logical hop. Each logical hop may compose multiple IP-level *physical* hops. Let N be total number of nodes in the system, then for any random pair of nodes, the number of logical hops is a function of N, denoted as $F(N)$.

The system we choose to evaluate is CAN. CAN organizes the logical space as a d-dimensional Cartesian space (a d-torus). The Cartesian space is partitioned into zones, with one or more nodes serve as owner(s) of the zone. Routing from a source node to a destination node boils down to routing from one zone to another in the Cartesian space. The routing cost, $F(N)$, between a random pair is $d/4 \times N^{1/d}$ logical hops. We assume that nodes populate the CAN logical space randomly; this is the default policy in CAN.

2.2 Namespace organization on top of P2P

There are various alternatives to build the namespace on P2P. The most straightforward option would be to hash the entire pathname of an object into a random key, and use it for placement and retrieval directly. For instance, in the case of CAN, */a/b* would hash to point $p_{/a/b}$, and */a/b/c* hashes to point $p_{/a/b/c}$, and so on so forth. Locating these objects then amounts to routing to the corresponding points in the logical space. This does not require any change to the underlying infrastructure. However, this works best for immutable namespace in practice. Consider that the path component *b* is changed to *b'*. This renaming operation not only renders that the directory */a/b'* be hashed to a different point and thus has to be relocated physically, but *all* pathnames following the directory *b* (now *b'*) are affected as well and therefore their corresponding objects have to be moved. Although it has been shown that rename is not a frequent operation in itself, such massive, uncontrollable relocation will cause severe instability in the system. Figure 1 helps to explain this phenomenon.

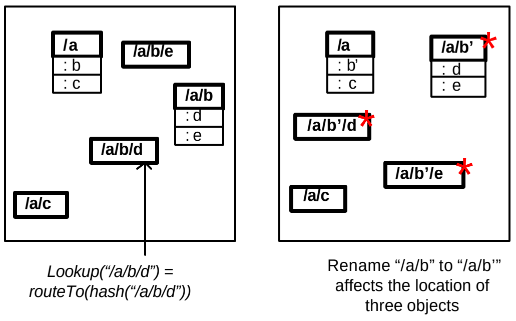

/a
: b
: c
/a/b/e
/a/b
: d
: e
/a/b/d
/a/c
Lookup("/a/b/d") = routeTo(hash("/a/b/d"))
/a
: b'
: c
/a/b'
: d
: e
/a/b'/d
/a/b'/e
/a/c
Rename "/a/b" to "/a/b'" affects the location of three objects

Figure 1: Using hashing on pathname alone can cause massive, uncontrollable relocation when rename occurs (objects with * attached are affected)

The problem here is that the placement decision creates binding with the structure of the namespace. Other hashing alternatives, such as hash on the content of directory objects, have similar (albeit reduced) problem.

Therefore, in order to have a namespace hierarchy that can cope with structural change, each directory must contain name of the children object as well as their location info (point in the Cartesian space in the case of CAN). This is very much like the directory structure in conventional file system, in which inode number is the routing key for the layers beneath. When location information is embedded, the placement of the objects becomes controllable, allowing us to explore locality in various namespace operations. (This is demonstrated in Figure 2, where the binding between a parent directory and all its sub-directories can be explored in *recursive* namespace lookup to reduce overall lookup cost.)

2.3 Lookup operation in the namespace

While the primary function of lookup is to locate the object, an implicit requirement for a general purpose namespace is to validate the path along the way. Other functionality such as right enforcement at directory level requires similar level-by-level resolution.

Lookup can be implemented in two different ways. The first, *iterative*, lets the client resolve one component at a time. This method is commonly used in local file system [10] in order to resolve over mount points. The other, *recursive*, hands over the complete path to the first directory, which resolves the first component and then passes the remaining path to the next directory, and so on so forth. The final result is then sent back directly to the client. These two approaches are shown in Figure 2. When a distributed system is built on P2P, different directories are very likely to reside on different nodes. Therefore, irrespective of the implementation, the unique directories (and thus unique nodes in the system) to be visited are the same. Obviously, the recursive approach reduces the total number of network hops and is more adequate in large-scale system where latency is high. To lookup an object *N* levels down, iterative requires *2N* network trips, comparing with *N+1* of recursive. For this reason, we choose the recursive method in this report.

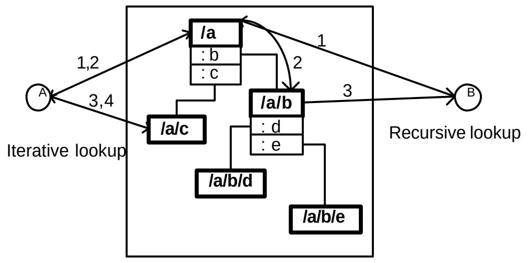


Figure 2: Two lookup procedures shown side by side. Node A performs iterative lookup, while node B performs recursive lookup. Each directory may reside on different nodes in the system. Links between objects are location information embedded in the directory entries. As shown, iterative incurs more network hops than recursive.

2.4 Cost of lookup

Having introduced namespace organization and lookup procedure, we can now discuss how lookup cost is computed.

For a given object, let *P* be the complete path (e.g., "/a/b/c"), and *D*=|*P*| be the length of the path. The total lookup cost can be expressed as $D \times \bar{h}$, where $\bar{h}$ is the number of average logical routing hops resolving *one* component. Assuming random node distribution in the logical CAN space, for any two nodes with the same logical distance, the physical routing latency between the two is roughly the same. As a result, we can compare various algorithms by their total logical routing hops. The two simple cases of lookup cost, each represents one extreme of the cost spectrum, are as follows:

- If we can compute the location of the object *a priori* (as is the case if hashing pathname is used to decide the object location), the so-called *zero* lookup bypasses all directories on the path and directly seek to the object. Since the query may be submitted from anywhere in the system, the total cost is equivalent to the routing cost between any two random pair of nodes in the system. The zero lookup cost is therefore $F(N)$.
- If, on the other hand, we allow any directories on P to reside *randomly* anywhere in the system, then resolving any component incurs the cost of routing between two random nodes. Therefore, the total cost is $D \times F(N)$. This solution, which we call *baseline*, has the best storage utilization.

$F(N)$ and $D \times F(N)$ represent the low and high bounds of lookup cost. Throughout the rest of the paper, we use L_b and L_0 to denote the cost of baseline and zero lookup, respectively. A good solution should strive to achieve lookup cost as close to $F(N)$ as possible, while keeping the storage utilization close to that of the baseline. In addition, the algorithm must be simple and efficient. This is especially important for large-scale peer-to-peer systems.

2.5 Discussion

It should be noted that in traditional distributed file system, path resolution results are often cached and thus lookup cost is paid only once. This has been particularly effective for small-scale system, where namespace structure does not change rapidly and/or the update cost is small. For a large scale P2P system, however, cached directory entries may get invalidated not only because the structure change, but also when their location (zone) change (i.e. the node hosting the original directory object). Furthermore, cache misses can be more expensive. What this means is while we still expect caching namespace resolution to be helpful, a system must not rely on caching alone but rather to start with a sound placement strategy to begin with.

3 The algorithms: *Radius-delta, Hill-climbing* and *Zoom-in*

As explained earlier, the total lookup cost can be expressed as $D \times \bar{h}$, where D is the path length, and $\bar{h}$ is the number of average logical routing hops resolving one component. The locality of the lookup procedure is inherent in resolving consecutive components. Therefore, to bring down $\bar{h}$, we can place a child object at a node that is close-by in routing with respect to the node hosting the parent object, subject to storage utilization constraint and decision complexity. This is the principle behind the *Radius-delta* and *Hill-climbing* algorithms. The third algorithm, *Zoom-in*, takes a somewhat different approach. The goal here is to quickly "zoom" into a small subset of nodes that host deep down sub-trees, making lookup cost irrelevant to the path length D.

3.1 Radius-delta

The idea here is to simply choose a small constant, r, which defines a small space within which a child object will be randomly placed, relative to the position of the parent. In the case of CAN, r is a small real number in the range of [0,1], for example 1/16.

There is no additional overhead in creation time: it's just a matter of picking a random point in the target space.

Under this algorithm, the average distance between a parent and one of its children is $r/2$ in CAN. The routing cost resolving one "component" is $r \times F(N)$. As a result, the total lookup cost is $D \times r \times F(N)$. Thus, lookup cost is r fraction of L_b and, theoretically, can always be reduced it by decreasing r.

With a balanced tree, the storage utilization with infinite number of nodes resembles a normal distribution centered at root. The height of the center depends on r: bigger r has a flat center and spreads out the distribution. Also, the deeper the tree relative to r, the more spread the distribution will be. This seems to imply that radius-delta by default have very poor storage balance. However, the system is not of infinite size. The effect of limited system size is to divide the "infinite" spread into chunks, and the total storage utilization can be found by "folding" the chunks on top of each other. Figure 3 illustrates these concepts. For the "folding" effect to take hold, $D \times r$ must be larger than 1 to allow the allocation "crawl" out of the boundary. Thus, a larger $D \times r$ has the net effect of smoothing up storage utilization, while at the same time increases lookup cost. As a result, there exists a tradeoff between lookup time and storage utilization.

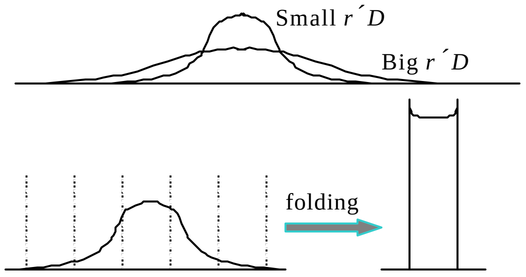


Figure 3: Storage utilization with radius-delta and the "folding" effect

3.2 Hill-climbing

In a P2P network, nodes typically exchange periodic heartbeats with its neighbors for maintenance purposes. Storage utilization of surrounding nodes can thus be made "free" by piggybacking such information along with the heartbeats. Guided with this knowledge, a node inspects its own storage utilization comparing with those of its immediate neighbors. If the minimum storage utilization of its neighbors is within a *threshold*, comparing with that of its own, it hosts the object immediately. Otherwise, it hands the job over to the one with the minimal utilization (breaking ties randomly) and the process starts there again. The default algorithm has a threshold of zero. A larger threshold value encourages parent-child collocation, at the cost of less even storage utilization distribution.

Lookup cost depends largely on parent-child distance. Consider the initial state of the system where there is no object, and assume the namespace is built recursively breadth-first. A "pile" will first emerge, with the later-comers laid on the surface. Since the surface increases gradually, the pace at which the "pile" expands also slows down. When the next level of hierarchies starts to build, new "shells" are put up and the "pile" crawls towards outbound. In reality, the actual tree creation order is arbitrary, and the hill-climbing algorithm always tries to place the object close-by, given the constraint of storage utilization. A deep and thin tree usually has short parent-child distance, whereas a fat and shallow tree is the opposite. As a result, lookup cost to leaf objects is insensitive to the tree shape.

The hill-climbing algorithm cannot always settle the placement of the object in one shot. If the parent directory is already in a "dip", the placement is immediate. If, on the other hand, the parent is at the top of a local "hill," the algorithm will roll "downhill" until a "dip" is found. In that case, creation takes longer time. A larger threshold tends to reduce the creation cost because it tolerates utilization deviations more. Another way to limit the creation cost is to introduce the time-to-live (TTL) value, which restricts the maximum number of hops the placement takes.

It is possible that multiple hills will emerge and, consequently, the total storage utilization becomes uneven. This is so because the optimization is always local, which is a fundamental property of the hill-climbing algorithm. When number of objects is much larger than the system size, the multiple-hill effect will be reduced. This is because the "pile" will eventually "overflow" the boundary and crawl backwards. Figure 4 demonstrates these concepts.

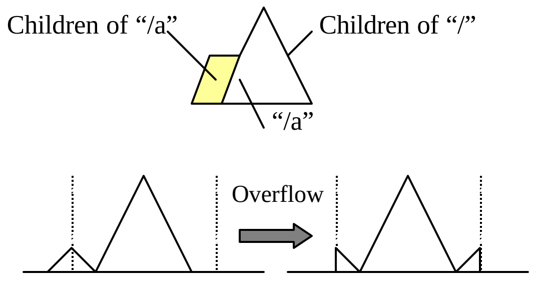


Figure 4: Storage utilization of hill-climbing algorithm

3.3 Zoom-in

While the previous two algorithms aim at bringing down $\bar{h}$, the goal of zoom-in is different. Zoom-in instead tries to minimize the impact of D and, in the extreme, renders it completely irrelevant.

With zoom-in, we always define the zone where a parent object lives, and sub-divide that zone into k (k is called the *zoom-in degree*) sub-zones in which we place the child objects in a random or round-robin fashion. This way, descending down the tree, the routing range will be recursively reduced, until the point where one single node now contains all the remaining sub-tree of a directory. From this point onwards, lookup becomes local operations to that node. Assuming sub-zones are perfect cubes and with fully balanced tree, we can prove that this algorithm can approach the performance of L_0:

For a d-dimensional CAN, assuming a zoom-in degree k, and a zone with average routing hops x, after zoom-in, the average routing hops of each of the k sub-zones will be $x*(1/k^{1/d})$. If we repeatedly sub-divide the sub-zones with the same zoom-in degree, after subdividing the zone y times, the average routing hops of the sub-zones will be $x*(1/k^{y/d})$. An upper-bound of the average lookup time is therefore, $F(N) * \sum_{y=0}^{\infty}\left(\frac{1}{k}\right)^{\frac{y}{d}}$, which is approximately $[k^{1/d}/(k^{1/d}-1)] \times F(N)$. With a large k, zoom-in approaches the performance of L_0.

There is no additional overhead involved in object creation. As long as the namespace tree is balanced, the storage utilization will also be perfect. But there is one catch: if the fan-out is smaller than k, then it's guaranteed that not all sub-zones will be populated. This is especially a problem if small fan-out occurs at higher level. Furthermore, zoom-in only works the most effectively if D is large (a shallow tree can be easily handled by radius-delta). Therefore, this algorithm is good for deep, balanced tree with fan-out a multiple of the zoom-in degree (especially at higher level). In other words, zoom-in is somewhat sensitive to tree shapes. We discuss remedies to that problem in later sections.

When *a priori* knowledge of the tree is available (for example a digital library), it is possible to do intelligent division of the zones (i.e, vary *k* and sub-zone sizes accordingly). The pseudo code of the algorithm is shown in Figure 5.

```
Step 1: Traverse the tree in post-order and assign a
weight to each node in the tree. The weight of a node
indicates the total amount of storage requirement for
the sub-tree rooted at the node.

Step2: call place(root, the entire Cartesian space);
The procedure 'place' and the auxiliary functions W
and Size are defined below:
  W: treenode → weight;// returns weight of a node
   Size: zone → double; // returns the size of a zone

place (r: treenode, z: zone) {
  Place r in z;
  Foreach (c :child of r) {
      zc = a new sub-zone of z,
        where Size(zc)/Size(z) equals to W( c )/W( r );
      place(c, zc);
  }
}
```

Figure 5 Pseudo code for distributing the name space according to the weight and structure of the tree

This algorithm consists of two steps: in the first step, the entire tree is traversed in post-order, and each node is assigned a weight that indicates the amount of storage requirements for the sub-tree rooted at each node. In the second step, the tree is traversed again and each node is placed into a zone whose size is proportional to the weight assigned to the node.[1]

One might argue that a tree whose structure is known beforehand can be handled by hashing the pathname. The difference here is that zoom-in can cope with structure change without massive relocation, and that it captures locality better because getting down the levels, objects start to cluster together rather than spread out.

3.4 Summary

The properties of the three algorithms can be summarized as the followings:

- By choosing small radius, radius-delta can arbitrarily reduce the lookup cost. However, the storage utilization improves only upon the product of the depth of the tree and the radius. As a result, there exists a tradeoff between lookup performance and storage utilization.
- Hill-climbing tries to minimize lookup cost given storage utilization constraint, and is insensitive to tree shapes. But it may take time to make placement decision, and require large object-to-system size ratio to populate system space.
- Zoom-in has the best theoretical performance, with lookup cost approaching that of zero lookup. However, it's more sensitive to tree shapes. Zoom-in with *a priori* knowledge of the tree structure is possible to attain good lookup performance as well as storage utilization.

The design of the above algorithms has taken the three requirements, performance, storage utilization and robustness, into account. Some of the desired properties can be found only through more in-depth analysis of the experiment results. As we will show shortly, these algorithms can be combined together for even better results.

4 Evaluation

We evaluate the three algorithms proposed by means of simulations. The primary goal of the experiment is to gain insight on how well the approaches perform, and secondly to identify potential optimization opportunities.

We choose CAN as the overlay network consisting of 1024 nodes (roughly about 1/100 of total objects for a given a tree), organized in a 2-d Cartesian space. Nodes populate this logic space uniformly. The details of experiment setup, workload and metrics of comparison are reported first, followed by the results and analysis.

4.1 Experiment setup

4.1.1 Namespace used

The namespace trees include both synthetic as well as real, active ones. In the synthetic class, two trees with dramatic different characteristics, *deep* and *fat*, are used. Deep is a binary tree containing objects spanning across 31 levels. The fanout in this tree grows slower, with fanout alternating between 1 and 2 per node as level grows. Fat tree has fan-out that doubles at each subsequent level, with initial fan-out of 4. Fat tree contains 100K objects with depth of 6. We gathered real active trees from two different sources. The first one is a namespace from an active server for software distribution in HP-Labs, and this tree has about 165K objects in total. The second active tree is web namespace that we generated from the proxy logs available from NLANR [11], which contains about 1M objects.

[1] When the shape of the tree changes causing a zone for a sub-tree to become over crowded, we can always allocate a new and less crowded zone for the new objects of the sub-tree that otherwise would fall into the over crowded area.

We use *d, f, h and w* as shorthand notations for these four trees from now on. Figure 6 shows the number of children at each level for these trees.

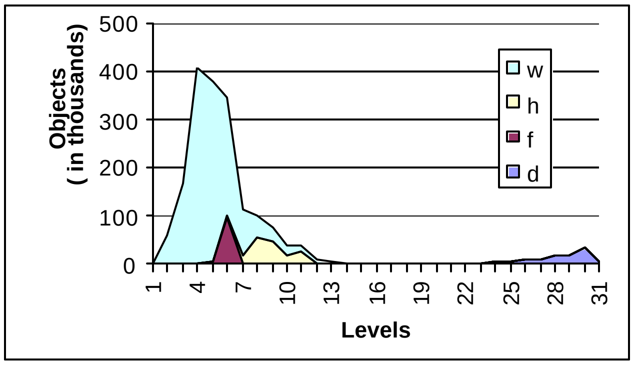


Figure 6: Shapes of the four trees used. (Where d, f, h and w refer Deep, Fat, HPL tree and Web Namespace respectively)

4.1.2 Access pattern

Namespace accesses correspond to two different kinds: those that construct the tree, and those that walk through the tree (lookup).

Since the log of tree creation is not available, to understand the effect of different tree creation order, we synthetically construct tree three different ways: depth first (DF), breadth first (BF) and random (R). Since the robustness against tree construction order is by itself an important issue, we dedicate a separate section to report its effect. In other parts of the evaluation, BF is used as the default tree construction order.

Access pattern is synthetic for all but the web namespace. In the case of synthetic access pattern, we randomly choose a set of paths from the processed tree and a set of nodes from the node space, to perform lookup. For the web namespace, the access pattern is directly taken from the proxy logs. We first hash the clients IP address to one of 1K locations and use the hashed value as node identifier to perform the lookup with the corresponding path that client accessed.

4.1.3 Metrics

For a given lookup operation, the cost is computed by counting logical hops routing to leaf objects. This gives us the direct measure of $\overline{h}$ -- number of logical hops resolving one segment in lookup. The number of hops "seeking" to the root is included. We average over 100 random samples; each is a pair of the query node and a leaf object. To give as fair a comparison as possible, we report the lookup cost, *L*, normalized by the zero lookup cost (L_0). The normalized baseline lookup costs (L_b) for the four trees are 27, 5.6, 8.7 and 5.2 for *deep*, *fat*, *hpl* and *web* respectively. Due to the irregularity of node's physical connectivity and position in the Internet, logical hop counts may not be perfectly proportional to the end physical latency observed. However, we believe *L* establishes a sound base for performance comparison in evaluating different algorithms.

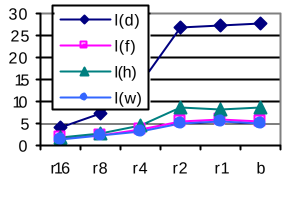
The storage utilization is the standard deviation amongst nodes. Similar to lookup performance, the storage utilization, *U*, is normalized by that of the baseline.

Wherever necessary, we also report the creation time *C*, which is the number of hops it takes before an object is finally placed. *C* represents the overhead in performing intelligent placement decision.

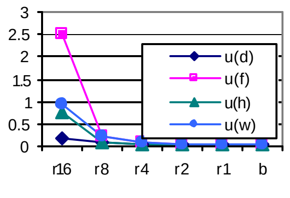
4.2 Results

Figure 7 shows the result of the basic radius-delta algorithm. For comparison purposes, we include the data of the baseline algorithm (data points labeled by "b"). We use altogether 5 different radiuses, from 1/16 to 1 (r*d* uses *1/d* as radius). There are clear tradeoffs between lookup cost versus storage utilization: *L* increases, whereas *U* decreases with radius. As described earlier, larger radius and *D* has the effect of "overflow" the boundary and even up the distribution. Consequently, *deep* has the best storage utilization, followed by *hpl*. Because *fat*, *hpl* and *web* are relatively shallow, lookup performances benefit from small radius for these trees.

For these workloads, radius of 1/8 is the most balanced between good lookup performance and reasonable storage utilization. On average, its lookup cost is about 4 times of L_0, 67% reduction over L_b.



(a) Lookup cost



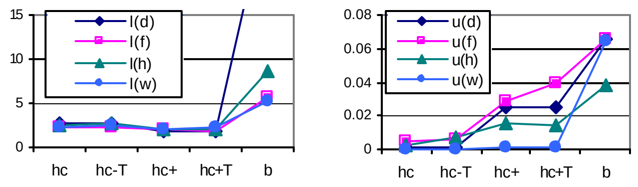
(b) Utilization

Figure 7: Radius-delta. *r*d means using radius delta of 1/r. The baseline results are the points on the "b" column.

Figure 8 depicts the result of the hill-climbing algorithm. We also studied variations with threshold and TTL. The threshold is number of objects as a fraction of the average objects per node. For example, if there are 100K objects in a system of 1K nodes, then average objects per node is 100. In this example, a threshold of 5% means a node will host an object unless one of its neighbors has 5 less objects. Because total number of objects is usually unknown at creation time, this threshold setting is not practical in reality, where an absolute storage utilization difference (weighted with bandwidth and other parameters) is more adequate. TTL is simply the maximum number of hops a placement will take before settling down. In Figure 8, *hc* is hill-climbing with infinite TTL; *hc-T* is hill-climbing with TTL equals to 10; *hc+* is hill-climbing with threshold of 5% and infinite TTL; *hc+T* is the same as *hc+* but with TTL=10. As before, baseline results are included.

The first observation to make is that, across the board, all variations achieve good storage utilizations as well as low lookup costs. Interestingly enough, the storage utilization is even better than baseline. It could also be observed that different trees make little effect. This is because for a given number of objects, a fat tree has low *D* and the average parent-to-child distance is greater; a deep tree is exactly the opposite. Setting non-zero threshold produce the same effect. Overall, lookup cost is around 3 times of L_0, achieving 78% reduction over L_b.

This robust performance comes with a slight cost of creation cost, since hill-climbing will look for storage under-utilization nearby. The creation costs for *hc* are 2.2, 4.2, 6.3 and 3.7 hops, for *deep*, *fat*, *hpl* and *web* respectively.

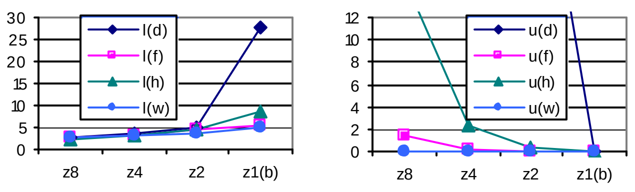


(a) Lookup cost (b) Utilization

Figure 8: Hill-Climbing algorithm.

Figure 9 gives the result of the zoom-in algorithm. The zoom-in degrees are is 8, 4, 2 and 1 (z*d* is zoom-in degree equals *d*). Note that zoom-in degree of 1 *is* the baseline algorithm.

Let us focus first on the lookup cost. As expected, zoom-in tends to be robust against different trees. Z4 seems to be good enough for these workloads, achieving lookup cost of 3.4 times of L_0, a 64% reduction over L_b. However, different trees have a significant impact on storage utilization. *Deep* with zoom-in degree of 8, populates a very small fraction of the system and its utilization *is* very poor (*U*=12K). However, as observed in Figure 6, the *web* tree has a very big fan-outs, as a result, storage utilization is excellent. This verifies our assumption that while zoom-in can attain the best theoretical lookup performance, its storage utilization is rather sensitive to different tree shapes.

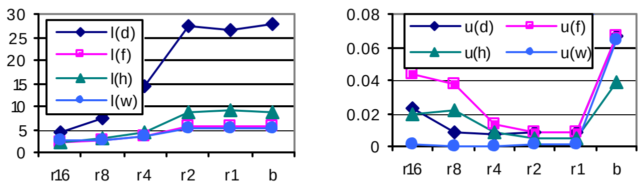


(a) Lookup cost (b) Utilization

Figure 9: Zoom-in algorithm

4.3 Variations

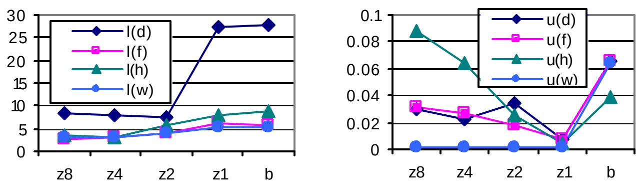
The hill-climbing algorithm can be a standalone tool to even up distribution. We apply this to radius-delta and zoom-in to see how much difference it makes in terms of storage utilization. Here, we use radius-delta and zoom-in as algorithms to make primary placement decision, and use hill-climbing to further fine-tune the placement according the storage utilization in the local context. Doing so may inadvertently reduce the lookup performance, since hill-climbing will move the placement to nearby underutilized nodes. Thus, we set the threshold to be 5%.



(a) Lookup cost: with hill-climbing (b) Utilization: with hill-climbing

Figure 10: Radius-delta with hill-climbing

Figure 10 shows the results of radius-delta, when applied with hill-climbing. Comparing with its non-hill-climbing counterparts, the storage utilization is greatly improved. Lookup costs increases are moderate. Since radius-delta has fairly good storage utilization to start with, it does not take hill-climbing too long to smooth the distribution: the average creation cost of r16, for example, is only 2 hops.

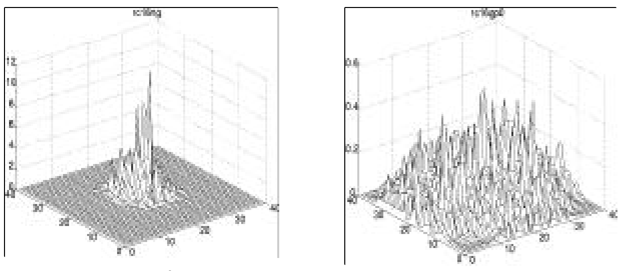


(a) Lookup cost: with hill-climbing (b) Utilization: with hill-climbing

Figure 11: Zoom-in with hill-climbing

Figure 11 shows that hill-climbing is very efficient to improve storage utilization for zoom-in as well. This comes with the cost of more creation time. Especially in z8 where storage utilization is the most imbalanced, it takes hill-climbing lots of time to even up utilization (6 creation hops). The impact on lookup is the most pronounced for *deep*: *L* with z8 increases from 2.7 to 8.2.

To gain more insight of the effectiveness of hill-climbing, Figure 12 plots the storage utilization of the radius-delta algorithm, before and after hill-climbing is applied. In the figure, x-axis corresponds to nodes in the system (node space is compacted into 40 chunks) and y-axis corresponds to the normalized storage utilization. The results are for *fat* tree with the smallest radius we experimented, 1/16. Recall that in radius-delta, storage utilization depends on *D´r*. Thus, this is the most unfavorable case to start with. As shown, the concentration is effectively mitigated after the hill-climbing is applied.



(a) Default (b) After

Figure 12: Effect of hill-climbing on storage utilization (radius-delta with r=1/16, on the fat tree).

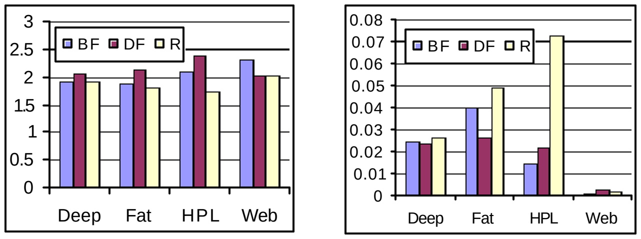
4.4 Robustness against tree creation order

In the above experiments, we have assumed a breath-first tree construction order. In reality, tree creation is far from predictable, not to say controllable. An important aspect of the placement algorithm is therefore how robust they are against different tree creation order.

For tree creation order to make a difference, the placement decision must have a dependency on the current layout status. As such, neither the basic radius-delta nor the zoom-in algorithm is sensitive to creation order: they depend on the overall structure *only*. However, the hill-climbing algorithm itself and the other two algorithms when combined with it are influenced by storage utilization at any given moment. To understand the impact of the tree creation, we use three forms of order, depth-first (DF), breadth-first (BF) and random (R). For random tree creation, we enumerate all the paths of each tree in random order, we then walk each component of the random paths and create an object if the component has not yet been created. We only report results of the following configurations:

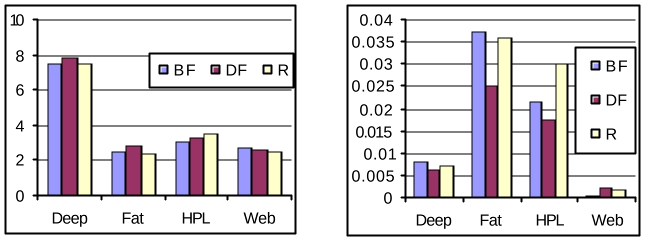
- Hill-climbing with threshold of 5 and 10 TTL.
- Radius-delta with *r=1/8*, combined with hill-climbing with threshold 5.
- Zoom-in with degree of 4, combined with hill-climbing with threshold 5.

We plot the lookup cost and storage utilization of DF, BF, and R as shown in Figure 13 through Figure 15. It can be observed that the order of tree creation has very little effect on the lookup cost and storage utilization for all the trees for the three experiment configurations. For the configuration with the hill-climbing algorithm alone, random tree creation slightly worsens the storage utilization for both the fat tree and the HPL tree. Both the fat and hpl trees are fat and shallow, and of relative small sizes. We believe that for small fat-trees, with a random strategy, there is a larger probability that multiple hills can emerge and consequently cause the total storage utilization uneven, whereas for a larger tree, such as the Web tree, the small hills are evened out because of the huge number of objects. We are still in the process of gaining in-depth understanding of the phenomenon. Nevertheless, it should be noted that even the worst case has better storage utilization than the baseline random case.



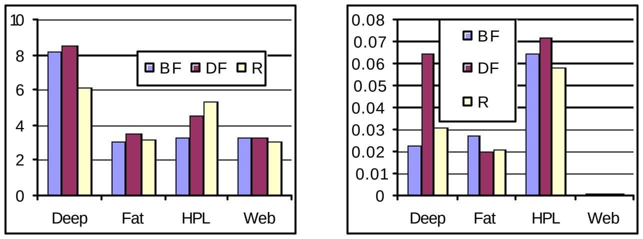
(a) Lookup cost: (b) Utilization

Figure 13: Lookup cost and Storage utilization for hill climbing using BF, DF and R tree creations



(a) Lookup cost: (b) Utilization

Figure 14: Lookup cost and Storage utilization for Radius-delta (8) using BF, DF and R tree creations



(a) Lookup cost: (b) Utilization

Figure 15:Lookup cost and Storage utilization for Zoom-in (4) BF, DF and R tree creations

4.5 Summary

In this section, we provide extensive experiment results on the three heuristic algorithms. Not surprisingly, in general, improving lookup performance comes at a cost of less even storage utilization distribution. Algorithms that try to balance the two calls for intelligent placement decision, which incurs additional overhead.

Our results indicate that the simple hill-climbing algorithm is robust and achieves the most balanced results overall, with moderate placement overhead. Hill-climbing is also very effective as a complementary tool to smooth out distribution for other algorithms. Radius-delta delivers fair performance, and its storage utilization can be improved quite easily using hill-climbing. The strength of zoom-in is for deep, balanced trees with fan-outs greater than zoom-in degree, and is demonstrated with the *web* namespace tree, which is shallow and has high fan-outs.

5 Discussion and other orthogonal mechanisms

We have assumed that storage distribution is at the granularity of object size. Other alternatives such as CFS [12] choose to treat the whole distributed storage space as a gigantic disk and therefore allocation is done at the block level. The difference in distribution granularity isn't the key issue, as resolving next component along the namespace path necessitates the access of component's internal data in any case – be it scattered on a number of blocks or contained in one object. Lookup performance only depends on the cost of seeking from one component to next.

In fact, we believe the algorithms we developed here is directly applicable not only as optimizations to improve lookup performance in block-based distributed file system on top of P2P, but can be extended to data blocks allocation as well. If an object is large, the blocks associated with it may spread across multiple nodes. Distribution of those blocks should take into account the access pattern of the application. If the access pattern isn't predictable, it will be safer to target the locality exhibited in sequential access and/or pre-fetching. Sequential access to a broad range of blocks is akin to "lookup" through a thin tree fan-out equal to 1. As such the blocks should be allocated close by, subject to storage utilization constraint. This is exactly the same assumption under which our algorithms for metadata distribution are developed.

Since lookup performance depends on system's routing capability, a number of obvious optimizations can be applied to shift the focus more towards storage utilization. For instance, we can use high-dimension CAN or other systems with O (log N) routing performance. Each node might have routing cache to keep direct routes to those frequently visited nodes. Alternatively, we can include a "hint" field in directory entry that speculates the node that keeps the child object. Apart from other well-known approaches such as caching and replication, directory aggregation, where an object contains multiple levels of underneath sub-directories, will also reduce the lookup cost by slashing *D*.

These approaches work well but only for namespace objects that are rarely modified. In a large-scale peer-to-peer system, enforcing consistency for directory objects that need to be accurate all the time is a sizeable challenge. On top of this, approaches such as directory aggregation will run into a phenomenon called "false-sharing."

Another vulnerable point of the above strategies has to do with the dynamic nature of P2P system. The side effect introduced when nodes come and go may also invalidate cached copies. Consequently, the system can't rely on caching alone, and a sound placement algorithm that relies on the default routing infrastructure *only* is highly beneficial. Our results support this conclusion, in that the lookup cost with these simple heuristics can be easily reduced by 60-70% over the naïve random algorithm.

6 Related work

Much works have gone into the issue of storage utilization in large-scale systems. Many of them are variations of hill climbing; this is the case in Farsite [13], CAN[4] and PAST[2]. The hill-climbing algorithm we proposed is guided by the same principle. In addition, we investigated a number of other algorithms. The unique contribution we make is that we treat the issue of storage utilization in conjunction with efficient hierarchical namespace in the peer-to-peer networks.

CFS [12] proposes an interesting alternative called "virtual server," which is to divide the resource of a physical server into multiple peers that participate in the peer-to-peer systems. The net result is that storage utilizations of multiple nodes in the overlay networks are aggregated. If those virtual servers are scattered sufficiently randomly, overall storage utilization in the physical world tends to be balanced. The tradeoff is that more states have to be kept per physical node. The focus there is on storage utilization, and the locality of file system operations and its impact on performance was not taken into account.

A number of systems are capable of building a distributed file system at object granularity [14, 15]. Lightweight protocols to construct namespace across geographically distributed sites are proposed in [16]]. In [17], qualitative arguments have been made about the gap between the hierarchical namespace and the flat P2P storage abstraction, pointing out that the "virtualization" property of P2P systems is incapable of taking advantage of the various locality exhibited by applications. Our view is consistent with theirs, and we have contributed not only with quantitative analysis but also algorithms to balance the tradeoff between performance and resource utilization.

7 Conclusion and Status

In this paper, we investigate the issue of establishing efficient hierarchical namespace in the flat storage space offered by peer-to-peer systems. To our knowledge, this is the first work that addresses this problem.

We found that, in general, there exists a tradeoff between lookup performance and uniform storage utilization distribution, and attempts to balance the two requirements in turn incur additional overhead for intelligent placement decision.

We derived a set of simple heuristics-based algorithms and verified them through experiments. Our approach is application driven, by taking full account of the locality exhibited in high-frequency operations. The design goal has been to arrive at algorithms and strategies that balance carefully between performance, storage utilization and robustness.

Our results indicate that the simple hill-climbing algorithm is robust and achieves the most balanced results overall, with moderate placement overhead. Hill-climbing is also very effective as a complementary tool to smooth out distribution for other algorithms. Simulation results show that our approaches can reduce the average lookup cost by 60-70% from the baseline.

Our planned future work include both advanced issues as well as problems we have not addressed properly:

- We plan to extend the algorithms and look into placement algorithms not only for metadata, but for data objects as well. We plan to investigate the placement algorithms for other popular distributed data structures.
- Adaptive schemes will serve many of the algorithms well if applied properly. For instance, in zoom-in, the way sub-zones are divided can be more intelligent; in hill-climbing, both TTL and threshold can be adjusted on the fly; lastly, in radius-delta, the radius can be modified as well.
- Some of the orthogonal optimizations we described could be combined with the current algorithms.
- Last but not the least, we'd like to see if these techniques can be extended to other peer-to-peer systems, and how much a difference it will make by varying system parameters.

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[+] This work was done while author was at Hewlett-Packard Laboratories.