LIGHT: A Query-Efficient Yet Low-Maintenance Indexing Scheme over DHTs

Yuzhe Tang, Shuigeng Zhou, *Member*, *IEEE*, and Jianliang Xu, *Senior Member*, *IEEE*

Abstract—DHT is a widely used building block for scalable P2P systems. However, as uniform hashing employed in DHTs destroys data locality, it is not a trivial task to support complex queries (e.g., range queries and k-nearest-neighbor queries) in DHT-based P2P systems. In order to support efficient processing of such complex queries, a popular solution is to build indexes on top of the DHT. Unfortunately, existing over-DHT indexing schemes suffer from either query inefficiency or high maintenance cost. In this paper, we propose LIGhtweight Hash Tree (LIGHT)—a query-efficient yet low-maintenance indexing scheme. LIGHT employs a novel naming mechanism and a tree summarization strategy for graceful distribution of its index structure. We show through analysis that it can support various complex queries with near-optimal performance. Extensive experimental results also demonstrate that, compared with state of the art over-DHT indexing schemes, LIGHT saves 50-75 percent of index maintenance cost and substantially improves query performance in terms of both response time and bandwidth consumption. In addition, LIGHT is designed over generic DHTs and hence can be easily implemented and deployed in any DHT-based P2P system.

Index Terms—Distributed hash tables, indexing, complex queries.

1 Introduction

Distributed Hash Table (DHT) is a widely used building block for scalable Peer-to-Peer (P2P) systems. It provides a simple lookup service: given a key, one can efficiently locate the peer node storing the key. The past few years have seen a number of DHT proposals, such as Chord [1], CAN [2], Pastry [3], and Tapestry [4]. By employing consistent hashing [5] and carefully designed overlays, these DHTs exhibit several advantages that fit in a P2P context:

- Scalability and efficiency: In a typical DHT of N peers, the lookup latency is $O(\log N)$ hops with each peer maintaining only $O(\log N)$ "neighbors."
- Robustness: DHTs are resilient to network dynamics and node failures that are common in large-scale P2P networks.
- Load balancing: Load balance in DHTs can be efficiently achieved thanks to uniform hashing.

As a result, several DHT services have been deployed in real life, such as the OpenDHT project [6] and the Kademlia DHT [7] for trackerless BitTorrent [8]. While DHTs are popular in developing various P2P applications, such as large-scale data storage [9], [10], [11], content distribution [12], and scalable multicast/anycast services [13], [14], they are extremely poor in supporting complex queries such as range queries and k-nearest-neighbor (k-NN) queries. This is primarily because data locality, which is crucial to processing such complex queries, is destroyed by uniform hashing employed in DHTs.

In this paper, we address a challenging problem of how to efficiently support complex query processing in *existing* DHT-based P2P systems. This problem is interesting to many real-life P2P applications/services. For example, some third-party developers may want to offer complex query facilities over the public OpenDHT service [6]. For another example, some P2P users may want the Kademlia DHT deployed in BitTorrent networks to support such range queries as "finding all trackers with torrents updated in the last three days."

To tackle the problem, an effective yet simple solution is to build indexes on top of existing DHTs (known as *over-DHT indexing paradigm* [15]). Several indexing schemes following this paradigm have recently been proposed, including Prefix Hash Trie (PHT) [15], [16], Range Search Tree (RST) [17], and Distributed Segment Tree (DST) [18]. Compared to another category of indexing schemes that entail development of new locality-preserved overlays (known as *overlay-dependent indexing paradigm*), over-DHT indexing schemes are more appealing to our problem for several reasons. First, over-DHT indexing schemes do not need to modify existing DHT infrastructures, whereas overlay-dependent indexing schemes would need to either change inner structures of existing DHTs or build extra overlays from scratch, both of which significantly increase the complexity of deployment. Second, following the design principle of layering [16], over-DHT indexing schemes are of great simplicity to design and implement; index developers can focus on the design of index structures only, while leaving system-related issues (e.g., overlay structure changes due to peer joins/departures, peer failure handling, and load balancing) to the underlying DHT. Third, since over-DHT indexing schemes rely only on the "put/get/lookup" interfaces of generic DHTs, they are

- *Y. Tang and S. Zhou are with the School of Computer Science, Fudan University and Shanghai Key Lab of Intelligent Information Processing, Shanghai, China. E-mail: {yztang, sgzhou}@fudan.edu.cn.*
- *J. Xu is with the Department of Computer Science, Hong Kong Baptist University, Kowloon Tong, Hong Kong. E-mail: xujl@comp.hkbu.edu.hk.*

Manuscript received 19 May 2008; revised 17 Nov. 2008; accepted 22 Jan. 2009; published online 6 Feb. 2009.
Recommended for acceptance by D. Papadias.
For information on obtaining reprints of this article, please send e-mail to: tkde@computer.org, and reference IEEECS Log Number TKDE-2008-05-0271.
Digital Object Identifier no. 10.1109/TKDE.2009.47.

applicable to any DHT-based P2P system. This is particularly appreciated given the fact that today's DHTs in use or in research differ significantly in their overlay structures [1], [3], [4]. In addition, to support multiple P2P applications, the over-DHT indexing paradigm allows for building multiple indexes on a single DHT infrastructure, thereby minimizing the overall system maintenance cost.

Two issues are critical to the performance of an over-DHT indexing scheme: *query efficiency* and *index maintenance cost*. In conventional applications where queries are more frequent than data updates, achieving query efficiency is considered the first priority. However, in P2P systems, peer joins and departures usually result in data insertions and deletions to/from the system; and the peer join/departure rate can be as high as the query rate [19], [20]. Such data updates incur constant index updates. Thus, the cost of index maintenance becomes a non-negligible factor in evaluating system performance. This perspective, however, is not realized in existing over-DHT indexing schemes. On the contrary, existing schemes improve query efficiency by sacrificing index maintenance cost as a trade-off. More specifically, in a distributed context, each peer maintains a local view of the global index; in order to achieve a better query performance, the common idea is to enlarge the local view and let each peer know more about the global index. For example, in PHT [15], each leaf node has direct access to its siblings. In DST [18], the index structure remains static and is made known globally. However, this static design inherently goes against the dynamic nature of P2P systems and easily leads to load imbalance. As an alternative, RST [17] allows for dynamic tree growth/contraction and further employs a broadcasting mechanism to maintain its global view. However, the index maintenance cost is prohibitively high as a single node split causes a broadcast to all other nodes, which may render the whole P2P system unscalable.

In this paper, we propose LIGhtweight Hash Tree (LIGHT)—a low-maintenance yet query-efficient scheme for data indexing over DHTs. Two novel techniques contribute to the superior performance of LIGHT: a clever *naming mechanism* that gracefully distributes the index structure over the underlying DHT, and a *tree summarization strategy* that offers each peer a scalable local view without incurring extra maintenance cost. LIGHT can efficiently support various complex queries, including range queries, min/max queries, and k-NN queries. As an over-DHT index, LIGHT requires no modification of the underlying DHT and hence possesses the virtues of simplicity and adaptability.

The contributions made in this paper can be summarized as follows:

- We propose LIGHT to address both query efficiency and maintenance efficiency for data indexing over DHTs.
- We develop efficient algorithms to process range queries, min/max queries, and k-NN queries based on the LIGHT index. We show through analysis that most of these queries can be supported with near-optimal performance (i.e., at most three more DHT-lookups than the optimum).
- We present two enhancements to LIGHT: an extensible technique for indexing unbounded data domains and a double-naming strategy for improving system load balance. To the best of our knowledge, LIGHT is the first over-DHT indexing scheme with such flexibility.
- We conduct extensive experiments to evaluate the performance of LIGHT. Compared with state-of-the-art indexing schemes, namely PHT [15], [16] and DST [18], LIGHT saves 50-75 percent of maintenance cost and substantially improves query performance in terms of both response time and bandwidth consumption.

The rest of this paper proceeds as follows: Section 2 surveys related work. Section 3 presents the LIGHT index structure, followed by a description of its lookup operation in Section 4. How to update the LIGHT index is explained in Section 5. Section 6 gives the algorithms for processing various complex queries based on the LIGHT index. Section 7 experimentally evaluates the performance of LIGHT. Enhancements to LIGHT are discussed in Section 8. Finally, Section 10 concludes this paper.

2 Related Work

P2P data indexing has recently attracted a great deal of research attention. Existing schemes can be classified into two categories: *over-DHT indexing paradigm* and *overlay-dependent indexing paradigm*. While over-DHT indexing schemes treat data indexing as an independent problem free from the underlying P2P substrates, overlay-dependent indexing schemes are intended to closely couple indexes with the overlay substrates.

In this section, we start with a brief overview of DHT overlays, followed by a detailed survey of existing P2P indexing schemes. Here, only structured P2P networks are considered.

2.1 Scalable DHT Overlays

In the design of DHT overlays, the primary concern is topological scalability in terms of two aspects: the *diameter*, which determines the bound of the hops of a lookup operation, and the *degree*, which determines the size of the routing table. Many proposed DHT overlays, including Chord [1], Pastry [3], Tapestry [4], and Bamboo [21], are based on the Plaxton Mesh [22], which achieves a diameter of $(\beta - 1)\log_\beta N$ and a degree of $\log_\beta N$. Here, β indicates the base of the DHT identifier space, for example, $\beta = 2$ in Chord. Another classical DHT, CAN [2], leverages the d-torus topology, which bears a diameter of $\frac{1}{2}dN^{\frac{1}{d}}$ and a degree of $2d$. From a graph-theory viewpoint, given diameter k and degree d, the number of nodes in a graph, N, is bounded by the Moore bound [23], that is, $N \leq 1 + d + d^2 + \cdots + d^k$. However, the Moore bound is not generally achievable. To move toward this optimal bound, several DHT overlays were inspired from the topologies of de Bruijn graphs [24], [25], butterfly graphs [26], and Kautz graphs [27]. A more thorough analysis of DHTs regarding scalability and fault tolerance can be found in [25].

2.2 Over-DHT Indexing Paradigm

In the over-DHT indexing paradigm, the DHT and data are loosely coupled by the keys (called DHT keys) generated from data records. Thus, a critical issue in the design of an over-DHT index is how to generate the DHT keys regarding data locality. In this category, the PHT [15], [16] is a representative solution for range queries, and is the most relevant scheme to our proposed LIGHT. Thus, below we first introduce PHT in detail. After that, we present other indexing schemes that support various queries for database and information retrieval applications.

PHT. As the first over-DHT index proposal, PHT supports indexing bounded one-dimensional data. Essentially, PHT partitions the indexing space with a trie (prefix tree) structure, where all data records are stored on leaf nodes. The trie structure is materialized over the DHT in a straightforward way—all tree nodes, including internal nodes and leaf nodes, are mapped into the DHT by directly hashing their labels of binary representation. A splitting/merging process is triggered for PHT whenever overload/underload occurs on leaf nodes. During the splitting process, two children with new labels are generated and hence all data records in the parent node need to be relocated according to the new labels. On the contrary, all data records in the children nodes would be relocated according to the parent's label during a merging process. The range query processing in PHT involves forwarding the query from the root to all candidate leaf nodes in parallel. To facilitate traversing candidate leaf nodes, PHT further maintains links between neighboring leaves, which however incur extra index maintenance overhead. Due to its simplicity and adaptability, PHT has been deployed in real-world applications [16]. RandPeer [28] applied PHT to a specific scenario—indexing membership data for QoS-sensitive P2P applications.

Other indexing schemes for range/k-NN queries. Several other studies have also investigated data indexing for range and k-NN queries, with their major focus being how to improve query latency by data replication. DST [18] replicates data records across all ancestors of a leaf node in the trie structure. To process a range query, DST decomposes the range into several subranges, each corresponding to an internal node. Since the trie structure is static and globally known, the internal nodes can be located by a single DHT-lookup, rendering the range query solved in $O(1)$ time. However, due to data replication in all ancestors, some high-level tree nodes could easily be overloaded. To address this issue, RST [17] employs a novel data structure, called Load Balancing Matrix (LBM), which organizes overloaded tree nodes into a matrix by further replication/partition. The nodes in LBM are mapped into the underlying DHT by hashing the internal labels as well as the matrix coordinates. As for query processing, due to query skewness, range queries are usually distributed only on a portion of the internal nodes (called *query band*). Based on this observation, a dynamic RST is proposed to adapt the tree structure to the current query band, making the index more efficient and the query load more balanced. To maintain a global view of this dynamic index, however, it relies on a broadcasting mechanism, which is bandwidth consuming and unscalable in terms of index maintenance cost.

To support multidimensional query processing, a naive solution is to employ multiple indexes, one for each dimension, as in RST. However, this solution not only increases index maintenance overhead but also complicates query processing. A later version of PHT [16] leverages space-filling curves to reduce dimensions. PRISM [29] employs reference vectors to generate DHT keys for multidimensional data. Following the tree maintenance method of RST, DKDT [30] embeds the k-d tree to support 2d similarity search. Chen et al. [31] suggested a framework for range indexing and proposed various strategies for mapping tree-based index structures into DHTs. Tanin et al. [32] superimposed the quadtree over the DHT for spatial indexing and querying. Each quadtree node is mapped into the DHT by hashing its centroid. While this paper focuses on one-dimensional data indexing, our proposed LIGHT scheme can nevertheless be extended to multidimensional data indexing by employing, for instance, dimension reduction techniques through space-filling curves [16].

Join and keyword queries. Join queries have attracted considerable research attention in P2P database systems [33], [34], [35]. While focusing on different types of equi-joins (e.g., two way versus multiway, snapshot versus continuous joins), they generally allocate data records by hashing both the names and values of join attributes, and aim to map the joining records (the records with the same value on the join attributes) to the same DHT node. For these P2P database systems, LIGHT can be seamlessly integrated by indexing the join columns to support general range-based joins, since the essence of such joins consists of range queries in a two-level nested loop.

While databases cope with structured data, there are other systems that deal with semistructured or unstructured data such as XML, RDF, and text. In these systems, processing effective keyword queries is essential. To support them over DHTs, a typical solution is to employ the Distributed Inverted Index (DII) [36]. In DII, the inverted index is superimposed over the DHT by directly hashing indexed keywords, and posting lists are intersected for conjunctive keyword search. The major problems of DII are that due to the Zipf distribution of text keywords, direct keyword hashing results in load imbalance, and due to destroyed data locality (particularly the keyword correlation) by hashing, intersecting posting lists consumes lots of bandwidth. To address these problems, many techniques have been proposed [36], [37], [38]. Following the framework of DII, Cai and Frank [39] and Galanis et al. [40] have also studied RDF and XML data indexing over DHTs.

2.3 Overlay-Dependent Indexing Paradigm

In the overlay-dependent indexing paradigm, the overlay substrate directly bears data locality. The existing schemes generally follow two approaches: Locality-Sensitive Hashing (LSH) and indexable overlays.

LSH-based indexing. Rather than using uniform hashing, LSH-based indexing employs locality-sensitive hashing to map data into the overlay in a locality-preserved way. By this means, some DHT overlays can directly support efficient range query processing [41], [42], [43], [44], [45]. Gupta et al. [46] applied LSH to DHT-based range indexing and provided approximate range query answers. For efficient similarity queries in P2P systems, LSH Forest [47] refined the traditional LSH by eliminating its data dependence. For keyword search, Joung et al. [48] proposed a novel indexing scheme, in which uniform hashing is replaced with Bloom filtering, and the underlying overlay is modeled as a multidimensional hypercube. To conduct keyword search, the hypercube is partially traversed by following a spanning binomial tree. Based on this framework, KISS [49] was developed to support prefix search. While preserving data locality, LSH-based indexing corrupts the uniform key distribution, which leads to load imbalance [50].

Indexable overlays. Indexable overlays make no use of full-fledged DHTs, but instead redesign the overlay from scratch and map data into it directly. The existing schemes in this category are based on various data structures. Skip graph [51] answers range queries based on a distributed structure originated from skip lists. PTree [52] and PRing [53] are based on distributed B-trees. BATON [54] is an overlay organized as a balanced binary tree. These overlays support one-dimensional data indexing. VBI-Tree [55] is a general framework that aims to map any existing index tree into BATON. It can index multidimensional data and support multidimensional range queries and k-NN queries. As a similar solution, SD-Rtree [56] uses a distributed balanced binary tree for spatial indexing. Mercury [57] uses a hierarchical ring structure to index multidimensional data. In these nonhash schemes, data locality is well preserved at the cost of deteriorated load balance. In recent years, many sophisticated balancing strategies have been proposed [58], [53], [59]. The basic idea is to first locate a light-loaded peer when overload occurs, and then to transfer load between them. These explicit balancing strategies cost much more in maintenance than the DHT hashing methods. In order to correctly locate a light-loaded peer, they typically require an extra overlay, say another skip graph, to index peer load information, which could double the overall overlay maintenance cost. In addition, the load transfer could also be consuming. By contrast, the DHT hashing methods are maintenance free—once data are allocated by uniform hashing, load balance is statistically guaranteed.

To summarize, the above over-DHT and overlay-dependent indexing schemes all have trade-offs in query/load balancing performance and practical deployment considerations. Although over-DHT indexing schemes are generally less efficient in query performance than overlay-dependent indexing schemes, by following the *layering* design principle, they are advantageous in terms of simplicity of deployment/implementation/maintenance and inherited load balancing as discussed previously. In practice, these issues are equally important to query performance [16]. Over-DHT indexing schemes are particularly favorable to the applications in which concerns about ease of implementation, deployment, and maintenance dominates the need for high query performance. The LIGHT index proposed in this paper follows the over-DHT indexing paradigm and outperforms all existing over-DHT indexing schemes.

3 The LIGHT Index Structure

In this section, we describe the LIGHT index structure and its mapping strategy to the underlying DHT. We remark that LIGHT is proposed to support complex queries over some existing DHTs, while exact-match queries can be directly and efficiently answered by the existing DHT infrastructure.

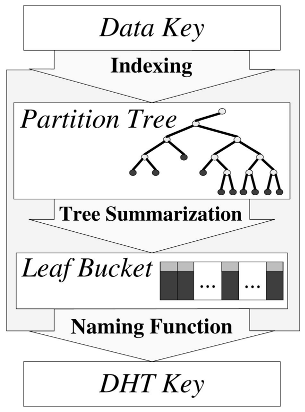


Fig. 1. LIGHT Indexing Architecture.

3.1 Overview

In the LIGHT index, a data unit is called a *record*, and each record is identified by a *data key* (denoted by δ).[1] We assume that the data keys to be indexed fall into a bounded one-dimensional space.[2] Without loss of generality, the space is set to $[0, 1]$ in this paper, and δ can be any floating number in it. On the other hand, to assign the records in the underlying DHT, each data record is associated with another key, called *DHT key* (denoted by κ). For a given DHT key κ, it is mapped to the peer whose identifier is less than but closest to $hash(\kappa)$. In a naive indexing scheme, one may set the DHT key directly to be the data key. However, this would destroy data locality, as mentioned earlier, and lead to inefficient support to complex queries. Thus, similar to other over-DHT indexing schemes, the main challenge of LIGHT is to find a mapping from data keys to DHT keys such that data locality is preserved with minimal maintenance cost. Fig. 1 gives an overview of the mapping operation in LIGHT. First, LIGHT employs a *space partition tree* to index data keys. Then, after the partition tree is decomposed and summarized in a data structure called a *leaf bucket*, LIGHT uses a novel naming function to map leaf buckets to DHT keys. In the following, we explain these two procedures in detail.

3.2 Space Partition Tree

As the name implies, the space partition tree (or simply *partition tree* for short) recursively partitions the data space into two equal-sized subspaces until each subspace contains fewer than θ_{split} data keys. Only leaf nodes store data records (or just data entries with pointers pointing to actual data records). Fig. 2 gives an example, where the data frequency histogram is shown at the bottom. We remark that here a space is always equally partitioned, regardless of the data distribution. This strategy makes the space indexed by each node known globally, which is essential to

1. A data record could contain the actual data item or the data entry consisting of the data key and a reference to the actual item, depending on whether LIGHT is the primary index.

2. The extension to an unbound space will be discussed in Section 8.

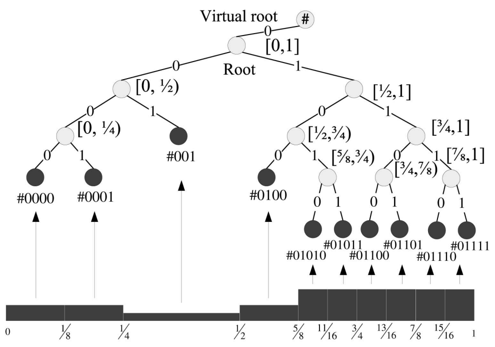


Fig. 2. An example of a space partition tree.

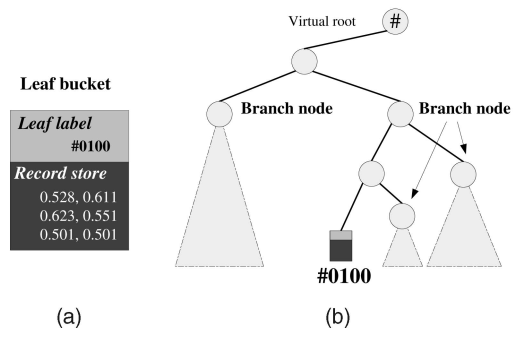


Fig. 3. Leaf bucket of the node $\#0100$. (a) Data structure. (b) Local tree of $\#0100$.

distributed query processing. Basically, the space partition tree is a binary tree with structural properties listed below:

- **Double Root.** Unlike a conventional binary tree, the space partition tree has two roots. The additional root, termed *virtual root*, is a virtual node above the ordinary one.
- **Completeness.** Every tree node, except the virtual root and leaf nodes, has two children, that is, every internal node has two children.

These two properties collectively guarantee that the number of leaf nodes equals the number of nonleaf nodes. Each node in the tree is assigned a unique label. The virtual root is labeled with a special character "#" in this paper. Each tree edge is labeled with a binary number, 0 (or 1) for the edge connecting the left (or right) child. As a special case, the edge between the virtual root and the ordinary root is labeled with 0. Then for any tree node, its label is the concatenation of the binary numbers on the path from the virtual root to itself (see Fig. 2). To facilitate our further discussions, we define some notations for the partition tree: λ denotes the label of a leaf node, while ω denotes the label of an internal node; Λ denotes the set of the leaves' labels, that is, $\Lambda = \{\lambda\}$, while Ω denotes the set of the internal nodes' labels, that is, $\Omega = \{\omega\}$.

3.3 Local Tree Summarization

Recall that data records are stored in leaf nodes; we need to map only leaf nodes to the underlying DHT. On the other hand, a bare leaf node lacks the knowledge of the overall tree structure, which, as we will see, is critical to complex query processing. Thus, we propose a distributed data structure, termed *leaf bucket*, to store data records and summarize the partition tree's structural information.

Each leaf bucket corresponds to a leaf node in the tree. As illustrated in Fig. 3a, a bucket consists of two fields: *leaf label*, which maintains the label λ of the leaf node, and *record store*, which keeps all data records of the leaf node. For each leaf bucket, the label λ provides a local view of the partition tree, which is called a *local tree*. As shown in Fig. 3b, the local tree of leaf node $\#0100$ consists of all its ancestors and their direct children (termed *branch nodes*). The label of any node in the local tree can be inferred directly from λ: the label of each ancestor is a prefix of λ, and the label of each branch node can be obtained by inverting the ending bit of a prefix of λ. According to the completeness property of the partition tree, all branch nodes must exist in the tree. Some branch nodes may contain a subtree, called the *neighboring subtree*, as depicted by shaded triangles in Fig. 3b. The structures of these neighboring subtrees are unknown in the current local tree, but are maintained by some other leaves' local trees.

From a global viewpoint, the local trees of all leaves together guarantee the partition tree's integrity. In other words, the leaf buckets collectively maintain the tree's structural information. Thus, the remaining issue is how to map each leaf bucket as an atomic unit to the DHT key, which is achieved by a novel naming function.

3.4 Naming Function

For a leaf bucket with label λ, the naming function $f_n(\cdot)$ generates its DHT key, that is, $\kappa = f_n(\lambda)$.

Definition 1. *For any leaf label $\lambda \in \Lambda$, the **naming function** is*

$$f_n(\lambda) = \begin{cases} p0, & \text{if } \lambda = p011*, \\ p1, & \text{if } \lambda = p100*, \\ \#, & \text{if } \lambda = \#00*, \end{cases}$$

where $p = \#0[0|1]*$.[3] That is, if λ ends up with consecutive 0s, $f_n(\lambda)$ truncates all the 0s in the end. Otherwise, it truncates all the 1s. For example, $f_n(\#01100) = \#011$ and $f_n(\#01011) = \#010$.

In a tree's view, each λ represents a leaf node, and interestingly, each $f_n(\lambda)$ represents a distinct internal node. Fig. 4 illustrates the intuition, in which each leaf bucket λ is "named" to an internal node $f_n(\lambda)$ by a dotted arrow, for instance, $f_n(\#01111) = \#0$. This nice property originates from the double-root and completeness properties of the partition tree. Recall that Λ and Ω represent the sets of labels for internal nodes and leaf nodes, respectively. We obtain the following theorem:

Theorem 3.1. *$f_n(\cdot)$ is a bijective mapping from Λ to Ω.*

Proof. We first prove that $f_n(\cdot)$ is indeed a mapping from Λ to Ω, and then prove that $f_n(\cdot)$ is bijective.

For $\forall\lambda \in \Lambda, f_n(\lambda)$ is a prefix of λ. By the labeling strategy, any prefix of λ represents an ancestor of the corresponding leaf, which in other words is an internal node. Therefore, $f_n(\cdot)$ is a mapping from Λ to Ω.

3. We here use the regular expression in which $[0|1]$ means 0 or 1, and $*$ means repeating zero or more times.

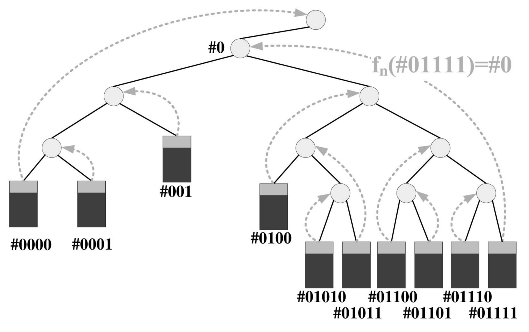


Fig. 4. Naming function and LIGHT.

As for the bijection, we prove a more concrete proposition: for $\forall \omega \in \Omega$, there is one and only one λ mapped to it. First consider the special case where ω is the virtual root; by definition, the leaf mapped to the virtual root is the leftmost leaf (i.e., the leaf labeled as $\#0*$). For any other internal node ω, there are two cases: ω ends up with a 0 (i.e., $\omega = \omega'0$), or with a 1 (i.e., $\omega = \omega'1$). For the first case, the leaf that is mapped to ω must be labeled as $\omega 11*$, because $f_n(\omega 11*) = f_n(\omega' 011*) = \omega' 0 = \omega$. By the labeling strategy, for a specific ω, there is one and only one leaf in Λ labeled as $\omega 11*$, that is, the rightmost leaf in the subtree rooted at ω. Similarly, for the second case, it is the leaf labeled as $\omega 00*$ mapped to ω, because $f_n(\omega 00*) = f_n(\omega' 100*) = \omega' 1 = \omega$. Therefore, $f_n(\cdot)$ is a bijective mapping from Λ to Ω. □

Since $f_n(\lambda)$ serves as the DHT key, Theorem 3.1 implies that the naming function actually organizes the internal structure of the partition tree in the DHT key space.

4 LIGHT LOOKUP

A fundamental service in LIGHT is the lookup operation:[4] given a data key δ, a LIGHT lookup returns the corresponding DHT key. Essentially, this is to find $\lambda(\delta)$, the label of the leaf bucket that covers δ, upon which we can apply the naming function $f_n(\cdot)$ to obtain the DHT key.

Recall that δ is a floating number in the range of [0, 1]. With the binary space partition tree, $\lambda(\delta)$ must be a prefix of δ in binary representation. For example, the binary representation of 0.4 is $0.01100\cdots$, then $\lambda(0.4)$ must be a prefix of $\#001100\cdots$, and in Fig. 2, $\lambda(0.4) = \#001$. Intuitively, $\lambda(\delta)$ is the longest prefix that corresponds to an existing (leaf) node in the space partition tree. Furthermore, if the maximal height of the tree is known,[5] denoted by D, the length of a possible prefix ranges from 2 to $D+1$. We denote the binary string by $\mu(\delta, D)$ and the set of possible prefixes of μ by $\Gamma(\mu)$ or $\Gamma(\delta, D)$. The lookup problem becomes how to find the longest label $\lambda(\delta)$ corresponding to an existing (leaf) node among the D candidate prefixes in $\Gamma(\mu)$. This is equivalent to finding the node that stores a leaf bucket covering δ.

4. In this paper, we may refer to LIGHT lookup as "lookup" for short, and for clarity the DHT-lookup remains its full name.

5. As done in PHT [15] and another range query scheme [60], D can be obtained by estimating the size and distribution of the indexed data set.

For efficient lookup, LIGHT employs a binary search algorithm, as illustrated in Algorithm 1. First, a LIGHT client initiates an interval for the lengths of candidate prefixes, between 2 and $D+1$ (line 2). In each loop iteration, it computes the median of the interval (line 4) and performs a DHT-get for the corresponding DHT key (line 6). If the DHT-get fails, meaning that the current prefix x corresponds to a nonexisting node and thus is too long, the client decreases the upper bound (line 8). Note that the prefixes between the DHT key $f_n(x)$ and the current prefix x are all mapped to $f_n(x)$ in the DHT key space. Thus, to speed up the search, the upper bound is set at $f_n(x)$ to avoid redundant checking. If the DHT-get succeeds and the returned bucket covers δ, the algorithm returns the current DHT key $f_n(x)$ (line 10); otherwise, if the returned bucket does not cover δ (line 12), meaning that x represents an ancestor of the target leaf and thus is too short, the lower bound is then increased to $f_{nn}(x, \mu)$, as defined below:

Definition 2. *For $\forall x \in \Gamma(\mu)$, the **next_naming function** $f_{nn}(x, \mu)$ is*

$$f_{nn}(x, \mu) = \begin{cases} p00*1 \in \Gamma(\mu), & \text{if } x = p0, \\ p11*0 \in \Gamma(\mu), & \text{if } x = p1, \end{cases}$$

where $p = \#0[0|1]*$. Intuitively, f_{nn} locates the first bit in the suffix of μ (with respect to x) that differs from x's ending bit; the value $f_{nn}(x, \mu)$ is then the prefix of μ, which ends up with this located bit. For example, $f_{nn}(\#001, \#0011100) = \#001110$.

Note that the prefixes between x and $f_{nn}(x, \mu)$ all share the same DHT key, namely $f_n(x)$. In the above example, $f_n(\#001) = f_n(\#0011) = f_n(\#00111) = \#00$. Thus, there is no point in searching the prefixes #0011 and #00111, since #001 has been checked.

Algorithm 1. LIGHT-lookup(data key δ)

```
1: $\mu \leftarrow$ binary-convert($\delta$)
2: lower $\leftarrow 2$, upper $\leftarrow D+1$
3: while lower $\leq$ upper do
4:     mid $\leftarrow$ (lower+upper)/2
5:     x $\leftarrow \mu$.prefix(mid)
6:     bucket_label $\leftarrow$ DHT-get($f_n$(x))
7:     if bucket_label=NULL then {a failed DHT-get}
8:         upper $\leftarrow f_n$(x).length
9:     else if bucket_label covers $\delta$ then {reach the target
           leaf bucket}
10:            return $f_n$(x)
11:    else {x is an ancestor of the target leaf node}
12:            lower $\leftarrow f_{nn}$(x,$\mu$).length
13: return NULL
```

An example. Consider a lookup of 0.9 with $D = 14$. Suppose LIGHT is as shown in Fig. 2 and the target bucket is the leaf #01110. Note that $\mu(0.9, 14) = \#01110011001100$. Initially, the lower bound is 2 and the upper bound is 15. LIGHT first tries the prefix of half length, that is, #0111001, and performs a DHT-get for $f_n(\#0111001) = \#011100$. Since the node responsible for #011100 does not exit, the DHT-get returns NULL, and the upper bound is decreased to 7 (the length of #011100). In the next try, a DHT-get is issued for $f_n(\#011) = \#0$. The node responsible for #0 is

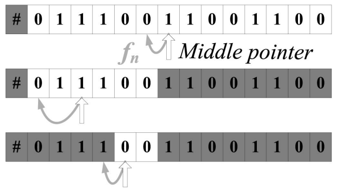


Fig. 5. An example of binary search in lookup operation.

then found, on which the leaf bucket label #01111 is stored (note that $f_n(\#01111) = \#0$). Thus, the DHT-get returns the leaf label #01111, which does not cover 0.9. In this case, the lower bound is increased to $f_{nn}(\#011, \#01110011001100) = \#01110$, while the upper bound remains at #011100. The next try is a DHT-get for $f_n(\#01110) = \#0111$, which reaches the target. This exemplar process is illustrated as in Fig. 5.

We analyze the complexity of the binary search algorithm in terms of the number of DHT-lookups. Here DHT-lookup is incurred by DHT-get only. Note that each DHT-get (in line 6) corresponds to a distinct $f_n(x)$, which is an element in the set $f_n(\Gamma(\mu))$. Since the cardinality of $f_n(\Gamma(\mu))$ is averagely the half the cardinality of $\Gamma(\mu)$ (i.e., $\frac{D}{2}$), the worst complexity of a LIGHT lookup operation is $\log(\|f_n(\Gamma(\mu))\|) \approx \log(\frac{D}{2})$ DHT-lookups. We notice that the binary search strategy is also applied in other over-DHT indexes [15], [60], but at a complexity of $\log D$. In comparison, thanks to the clever naming function, LIGHT makes an improvement of $\frac{\log D - \log D/2}{\log D} = \frac{1}{\log D}$.[6]

Lookup in presence of peer failures. In the presence of severe peer failures where data availability cannot be guaranteed by underlying DHTs,[7] the binary search might be misled by regarding a failed node as a nonexisting node. In the previous example, the search range is $[\#, \#011100]$ right before the second DHT-get for $f_n(\#011) = \#0$. For DHT-get($f_n(\#011)$), if the peer responsible for #0 is temporarily down, the algorithm will falsely consider the current prefix too long and hence contract the search range to the lower half $[\#, \#0]$. Thus, the algorithm would end up with no leaf found to cover 0.9. In this case, an additional recovery procedure can be invoked. The recovery procedure will trace back to the most recently failed DHT-get, which must be caused by a node failure, and adjust the search range there from the lower half to the upper half. In the above example, it will adjust the search range from $[\#, \#0]$ to $[\#01110, \#011100]$. Then the binary search will be resumed over the new search range $[\#01110, \#011100]$, and finally reach the target leaf #01110. This recovery procedure can be recursively invoked in the case of multiple peer failures until the target leaf is found (as long as the target leaf is not unavailable).

6. For indexing data sets of less than 1 billion records, the value of D is usually smaller than 30, which makes $\frac{1}{\log D}$ a non-negligible fraction.

7. In case of mild peer failures, DHTs can guarantee data availability through techniques like data replication, and does not affect the lookup operations.

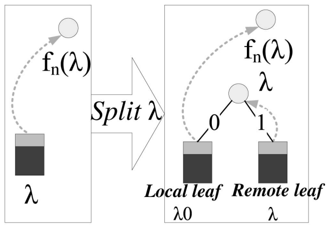


Fig. 6. Leaf split in LIGHT when $\lambda = p10 * 0$.

5 LIGHT Maintenance

Unlike overlay-dependent indexes that would update their structures with *network structure* changes caused by system dynamics (i.e., peer joins/departures/failures), the LIGHT index only needs to handle *data* updates while leaving network structure changes to the underlying DHT. In this section, we present the LIGHT index maintenance algorithms for data insertions and deletions.

5.1 Data Insertion and Leaf Split

Inserting a data record into LIGHT involves a LIGHT lookup and a possible leaf split process. More specifically, for a data key δ, LIGHT performs a lookup to locate the target leaf bucket $\lambda(\delta)$, and then calls a DHT-put to place the record there. However, if the leaf bucket $\lambda(\delta)$ is already full (i.e., containing θ_{split} or more records), the insertion will split the bucket and generate two new leaves. In LIGHT, one leaf bucket will stay on the current peer, denoted as the *local leaf*, while the other one, denoted as the *remote leaf*, will be pushed out to some other peer. The local leaf is not pushed out and consumes no bandwidth overhead. This nice property, which we call *incremental leaf split*, is explained in Theorem 5.1.

Theorem 5.1. *Consider a leaf labeled with λ, which would be split into two nodes, labeled with $\lambda 0$ and $\lambda 1$. The naming function maps one still to $f_n(\lambda)$, and the other one to λ.*

Proof. We consider the case where λ ends with 0 (the case where λ ends with 1 can be proved similarly). Without loss of generality, we assume that $\lambda = \#0[0|1] * 100*$. After the split, the labels of the two new nodes, $\lambda 0$ and $\lambda 1$, are $\#0[0|1] * 100 * 0$ and $\#0[0|1] * 100 * 1$, respectively. Obviously, $f_n(\lambda 0) = f_n(\#0[0|1] * 100 * 0) = f_n(\#0[0|1] * 100*) = f_n(\lambda)$, and $f_n(\lambda 1) = f_n(\#0[0|1] * 100 * 1) = \lambda$. □

Theorem 5.1 directly leads to incremental leaf split: by LIGHT's mapping strategy, the previous leaf bucket λ is mapped to the peer with identifier $hash(f_n(\lambda))$. After splitting, the local leaf bucket is still named to $f_n(\lambda)$ and thus remains on the same peer. The other one, which is named to λ, gets a new name and is mapped to some remote peer. Such a process is illustrated in Fig. 6.

Algorithm 2 formally describes how the leaf bucket splits in a distributed manner. The procedure $leafsplit(b)$ is invoked whenever a leaf bucket b is found containing θ_{split} or more records during a data insertion. In order to split, it first checks the value of the leaf label λ (line 2) and accordingly updates the labels of b and the remote leaf bucket rb (lines 3-7). Since the data space is partitioned, the records are reassigned into b and rb (line 8). After updating

b locally, the algorithm calls a DHT-put to place the bucket rb onto some remote peer (line 10). During the whole process, the algorithm relies only on local knowledge and consumes one DHT-lookup (in the DHT-put).

Algorithm 2. Leaf-split(leaf bucket b)

```
1: $\lambda \leftarrow b.leaflabel$
2: **if** $\lambda = p011*$ **then**
3:     $rb.leaflabel \leftarrow \lambda 0$ {rb is the remote leaf bucket}
4:     $b.leaflabel \leftarrow \lambda 1$
5: **else**
6:     $rb.leaflabel \leftarrow \lambda 1$
7:     $b.leaflabel \leftarrow \lambda 0$
8: Add corresponding records to $rb$ and delete them in $b$.
9: Locally write $b$ back to the disk of current peer.
10: DHT-put($\lambda, rb$)
```

5.2 Data Deletion and Leaf Merge

To remove the data key δ, LIGHT, similar to data insertion, first performs a lookup to locate the leaf bucket that covers δ, say $\lambda(\delta)$. It then executes a local deletion operation to remove the corresponding record.

Algorithm 3. Leaf-merge(leaf bucket λ)

```
1: if $load(\lambda) < \theta_{merge}$ then
2:     $\lambda_s \leftarrow$ DHT-lookup($f_s(\lambda)$)
3:     if $length(\lambda) = length(\lambda_s)$ then
4:       if $load(\lambda) + load(\lambda_s) < \theta_{split}$ then
5:         if $\lambda = f_n(\lambda_s)$ then
6:           Push bucket $\lambda_s$ to $\lambda$.
7:         else {this is when $\lambda_s = f_n(\lambda)$}
8:           Push bucket $\lambda$ to $\lambda_s$.
9:         local-merge($\lambda, \lambda_s$)
```

Data deletion may further lead to a merge of leaf buckets if the number of records (called *load* for brevity) contained in the leaf and its sibling drops below θ_{split}. Algorithm 3 illustrates the leaf merge operation. In line 1, we predefine a merge threshold θ_{merge}, which determines whether to trigger a probe of its sibling's load (line 2). The sibling node is located by a *sibling function* f_s, which is defined as below:

Definition 3. *For a leaf bucket labeled with λ, the* ***sibling function*** *$f_s(\lambda)$ returns the DHT key of its sibling.*

$$f_s(\lambda) = \begin{cases} f_n(p0), & \text{if } \lambda = p1, \\ f_n(p1), & \text{if } \lambda = p0, \end{cases}$$

where $p = \#0[0|1]*$.

The algorithm proceeds to check whether λ's sibling is a leaf node, that is, whether the retrieved label λ_s for the sibling has the same length as λ (line 3). If this is true and their total load is lower than θ_{split}, the actual merge operation is started (lines 5-9). Note that in the push operation, there is no need to perform the DHT-lookup for $f_s(\lambda)$ again, since it was already found in line 2. Thus, only one DHT-lookup is incurred for each data deletion operation.

By the definition of our space partition tree, $\theta_{merge} = \theta_{split}$. In practice, however, to avoid unnecessary checking and hence save bandwidth consumption, θ_{merge} can be set to a fraction of θ_{split} (e.g., half of θ_{split}), though this would deteriorate the index consistency.

5.3 Analysis of Tree Maintenance Cost

5.3.1 Cost Model

Before analyzing the tree maintenance cost, we propose a cost model reasonable for over-DHT indexing schemes. A P2P network is characterized by abundant local resources. That is, a typical P2P network holds ample resources (e.g., local disk storage and CPU power) at the network edges. By contrast, the internetwork resource, namely the bandwidth, is relatively rare and thus critical in a P2P network. Therefore, to capture the P2P network cost, we consider only the bandwidth consumption in the analysis. For an over-DHT indexing scheme, two operations are bandwidth consuming: *DHT-lookup* and *data movement* (i.e., transferring data records from one peer to another via a physical connection, like TCP or UDP). We assume that moving each data record costs $\imath$ units and each DHT-lookup costs $\jmath$ units. The value of $\imath$ is determined by the size of a data record—the larger the data record, the higher the cost incurred for data transferring. The value of $\jmath$ is determined by the scale of the underlying P2P network—for a P2P network with more peers, a DHT-lookup incurs more physical hops (typically at complexity of $O(\log N)$), which leads to a larger $\jmath$.

5.3.2 Maintenance Cost

In the interest of space, only data insertion is discussed here; data deletions can be similarly analyzed. As discussed earlier, each data insertion involves a LIGHT lookup and a possible leaf split. A LIGHT lookup incurs $\log(D/2)$ DHT-lookups and movement of one data record.

For each leaf split in LIGHT, only one DHT-lookup is incurred, yielding the DHT-lookup cost of $\jmath$; the data-movement cost is proportional to the size of the remote leaf bucket. Note that for a pair of remote and local buckets, their sizes sum to θ_{split}. Let the size of the remote bucket be a fraction of θ_{split}, denoted as $\alpha \cdot \theta_{split}$, where α is a normalized factor in $[0, 1]$. The size of the local bucket is thus $(1 - \alpha) \cdot \theta_{split}$. For a specific split, the very value of α is determined by the local data distribution on the splitting node. For a large enough tree, while the data skewness does affect the global tree structure, the local data distribution within a leaf node is likely to be uniform, yielding an average α equal to $\frac{1}{2}$. Thus, the average data-movement cost per split is $\frac{1}{2}\theta_{split} \cdot \imath$. In all, the average cost for one leaf split in LIGHT, denoted as Ψ_{LIGHT}, is

$$\Psi_{LIGHT} = \frac{1}{2}\theta_{split} \cdot \imath + 1 \cdot \jmath.$$

We compare the maintenance cost for a leaf split with PHT [15], which is the state of the art with respect to maintenance efficiency. In PHT, an index tree similar to the space partition tree is maintained and, as mentioned, its mapping to the underlying DHT is quite straightforward—all the tree nodes (including the internal nodes) are mapped directly by its label. As a result, one split produces two leaf buckets with new labels, which are both mapped to some remote peers. This incurs two DHT-lookups and movement

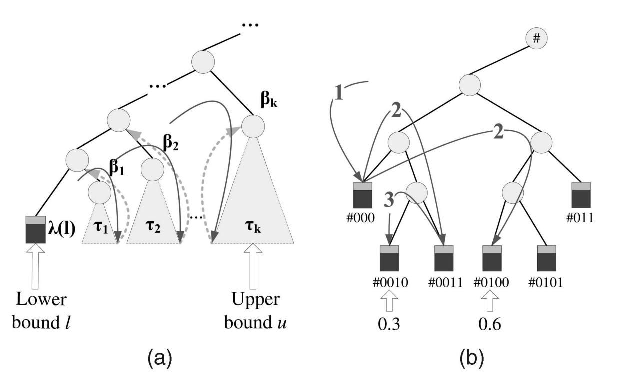


Fig. 7. Range query processing. (a) Local tree of λ and the recursive forwarding. (b) An example.

of θ_{split} data records. Additionally, a split incurs two extra DHT-lookups to update its B+ tree leaf links [15]. Altogether, the bandwidth cost for a PHT split is

$$\Psi_{PHT} = \theta_{split} \cdot \imath + 4 \cdot \jmath.$$

In comparison with PHT, LIGHT saves the maintenance cost for leaf split by

$$1 - \frac{\Psi_{LIGHT}}{\Psi_{PHT}} = \frac{\frac{1}{2} \cdot \gamma + 3}{\gamma + 4},$$

where $\gamma = \frac{\theta_{split} \cdot \imath}{\jmath}$. This savings ratio can range from 50 to 75 percent, depending on the value of γ.

6 Complex Queries

In this section, we discuss the processing of various complex queries over the LIGHT index, including range queries, min/max queries, and k-NN queries.

6.1 Range Queries

Given two bounds, l and u, a range query returns all data records whose keys fall in the range of $[l, u)$. Thanks to the local tree, LIGHT can support range query processing at near-optimal cost. To illustrate how it works, we start with a simple case.

6.1.1 A Simple Case

In this case, the query issuer happens to be the leaf bucket containing one of the range bounds. Without loss of generality, we assume that it is the lower bound l. As explained earlier, the leaf bucket can construct a local tree, as illustrated in Fig. 7a. This figure shows the lower bound leaf $\lambda(l)$ and all its right neighboring subtrees, denoted by $\tau_1, \tau_2, \ldots$. In general, the subtree τ_i covers the data space $[pv_i, pv_{i+1})$, where partition value pv_i is the lower bound of the space covered by τ_i. Further denote the right branch nodes by $\beta_1, \beta_2, \ldots$, which can be inferred based merely on the knowledge of $\lambda(l)$:

Definition 4. *For a tree node labeled with x, the* ***right neighbor function*** *$f_{rn}(x)$ returns the label of its nearest right branch node. For example in Fig. 7a, $f_{rn}(\lambda(l)) = \beta_1$, $f_{rn}(\beta_i) = \beta_{i+1}$. The right neighbor function is defined as follows:*

$$f_{rn}(x) = \begin{cases} x, & \text{if x} = \#011*, \\ p1, & \text{otherwise x} = p01*, \end{cases}$$

where $p = \#0[0|1]*$. In the case where $x = \#011*$, the tree node x already lies rightmost in the LIGHT tree and f_{rn} maps it to itself. We can similarly define the ***left neighbor function*** *$f_{ln}(x)$:*

$$f_{ln}(x) = \begin{cases} x, & \text{if x} = \#00*, \\ p0, & \text{otherwise x} = p10*. \end{cases}$$

Using $f_{rn}(x)$, the leaf bucket $\lambda(l)$ can locally infer all β_is. The query range $[l, u)$ bounds the rightmost branch node β_k, whose neighboring subtree τ_k covers the range's upper bound u, as depicted in Fig. 7a. We distinguish two cases: 1) the query's upper bound u is smaller than the upper bound of the space covered by τ_k; 2) u is exactly the same as τ_k's upper bound. For Case 1, the arrows in Fig. 7a illustrate how leaf bucket $\lambda(l)$ forwards the query to recursively traverse all the leaves in the range $[l, u)$: it forwards the query to the rightmost leaves in all τ_is for $i = 1, 2, \ldots, k-1$ and the leftmost leaf in τ_k. The former forwarding is done by a DHT-lookup of $f_n(\beta_i)$ (i.e., the parent of β_i) because, as shown in the figure, the rightmost leaf in τ_i is named to $f_n(\beta_i)$, while the latter forwarding is done by a DHT-lookup of β_k because the leftmost leaf in τ_k is named to β_k. The current query range $[l, u)$ is then decomposed into disjoint subranges for these next-hop leaves, specifically, $[pv_i, pv_{i+1})$ for the rightmost leaf in τ_i $(i = 1, 2, \ldots, k-1)$ and $[pv_k, u)$ for the leftmost leaf in τ_k. For Case 2, the forwarding process is similar except that $\lambda(l)$ forwards the query to the rightmost leaves in all τ_is for $i = 1, 2, \ldots, k$. The similar forwarding procedure can be recursively invoked until the leaf completely covers the queried subrange. Algorithm 4 formally describes the recursive forwarding strategy for the simple case.

Algorithm 4. Recursive-forward(bucket b, range R)
```
1: $leftwards \leftarrow (b.leaflabel = p011*)$
2: $\beta \leftarrow b.leaflabel$
3: loop
4:     if $leftwards = true$ then
5:         $\beta \leftarrow f_{ln}(\beta)$
6:     else
7:         $\beta \leftarrow f_{rn}(\beta)$
8:     $inv \leftarrow$ interval($\beta$) {compute the interval covered by
           branch node $\beta$}
9:     if $inv \cap R = NULL$ then
10:        return
11:    else if $inv \subseteq R$ then
12:        $nextbucket \leftarrow$ DHT-lookup($f_n(\beta)$)
13:        recursive-forward($nextbucket, inv$)
14:    else
15:        $nextbucket \leftarrow$ DHT-lookup($\beta$)
16:      if $nextbucket = NULL$ then {a failed DHT-lookup}
17:          $nextbucket \leftarrow$ DHT-lookup($f_n(\beta)$)
18:      recursive-forward($nextbucket, inv \cap R$)
19:      return
```

For complexity, one point noteworthy is that during the whole recursive procedure, at most one DHT-lookup could possibly fail. It only occurs when LIGHT forwards the query to DHT key β_k and the β_k corresponds to a leaf node.

For all the subqueries forwarded to $f_n(\beta_i)$, they could not fail, because there must exist one leaf node in τ_i which is named to $f_n(\beta_i)$.

6.1.2 General Case

In the general case, the query issuer can be any leaf bucket. As described in Algorithm 5, after receiving the range query $R = [l, u)$, the leaf locally computes the *lowest common ancestor* that covers R, abbreviated as LCA. It then forwards the query by a DHT-lookup of $f_n(LCA)$. We discuss three possible cases: 1) The DHT-lookup has failed (line 3), implying that range R is so small that a single leaf completely covers it. In this case, the range processing is reduced to a lookup operation. 2) The returned leaf bucket overlaps the query range (line 6), implying one range bound must be in this leaf bucket. This is the simple case we discussed above. 3) The returned leaf bucket does not overlap the query range (line 8). In this case, the query range is subdivided and, respectively, forwarded to LCA's children, namely $LCA0$ and $LCA1$. Note that each of the leaves named to $LCA0$ and $LCA1$ must cover one bound of the corresponding subrange. Thus, the processing of both subsequent queries can follow the simple-case strategy.

Algorithm 5. General-forward(range R)

```
 1: $LCA \leftarrow$ computeLCA($R$).
 2: $bucket \leftarrow$ DHT-lookup($f_n(LCA)$)
 3: if $bucket = NULL$ then {a failed DHT-lookup}
 4:     return LIGHT-lookup($R.lowerbound$)
 5: else
 6:     if $bucket$ overlaps $R$ then {turn into the simple case}
 7:         return recursive-forward($R, bucket$)
 8:     else
 9:         $bucket \leftarrow$ DHT-lookup($LCA0$)
10:         $result_0 \leftarrow$ recursive-forward
              ($R \cap bucket.range, bucket$)
11:         $bucket \leftarrow$ DHT-lookup($LCA1$)
12:         $result_1 \leftarrow$ recursive-forward
              ($R \cap bucket.range, bucket$)
13:         return $result_0 \cup result_1$
```

An example. Consider the range query $[0.3, 0.6)$ on the tree shown in Fig. 7b. Any leaf bucket receiving the query locally calculates the LCA to be $\#0$ and performs a DHT-lookup of $f_n(\#0) = \#$. The returned leaf bucket is $\#000$, whose range does not overlap the queried range (i.e., Case 3). As mentioned, the queried range is then subdivided and forwarded to DHT keys $\#00$ $(= f_n(\#001) = f_n(f_{rn}(\#000)))$ and $\#01$ $(= f_{rn}(\#001))$, to which leaf buckets $\#0011$ and $\#0100$ are respectively named. Bucket $\#0011$ has its bound value of 0.5 in the queried range and hence the recursive forwarding process then applies; bucket $\#0011$ further forwards it to $\#001$ $(= f_n(f_{ln}(\#0011)))$, which is the name of bucket $\#0010$. After that, all leaf buckets in the range $[0.3, 0.6)$ are found.

6.1.3 Complexity

Suppose the query range is distributed on B leaf buckets. We here consider only the case where $B >= 2$ (i.e., Cases 2 and 3 discussed in the last section). In general forwarding (Case 3), there is at most one DHT-lookup that returns a leaf bucket not overlapping the range. Moreover, as explained in Section 6.1.1, in the procedure of each recursive forwarding, there is at most one failed DHT-lookup. Therefore, a total of three extra DHT-lookups can possibly occur, that is, the LIGHT-based range query costs at most $B + 3$ DHT-lookups, which is close to the optimal performance (i.e., B DHT-lookups).

6.2 Range Queries with Lookahead

To further reduce the query latency, we propose a parallel processing algorithm. The basic idea is that each recursive forwarding in the range query looks one step ahead. That is, for each branch node β_i $(i = 1, 2, \ldots, k)$ in Fig. 7a, the bucket $\lambda(l)$ forwards the query not only to $f_n(\beta_i)$ but also to β_i. By this means, each recursive forwarding can explore the neighboring subtree by two levels (instead of one level as in the original algorithm). Therefore, total latency can be reduced by a factor of two. However, the lookahead can increase the number of DHT-lookup failures, typically from 3 to $B/2$. This is because in the worst case each lookahead may result in a DHT-lookup failure. As such, the lookahead strategy trades bandwidth overhead for shorter query latency. In general, if we look h steps ahead, the average latency can be reduced by a factor of $h + 1$, while the number of DHT-lookups is increased by h times. In practice, the user can tune the parameter of h based on his/her performance preferences.

6.3 Min/Max Queries

The min (max) query returns the smallest (largest) data key in the data set. Interestingly, LIGHT supports processing a min/max query at constant cost, owing to its nice naming function. More specifically, the query complexity is one DHT-lookup only.

Theorem 6.1. *In LIGHT, a DHT-lookup of $\#$ returns the smallest key, whereas a DHT-lookup of $\#0$ returns the largest key.*

Proof. The leaf bucket containing the smallest data key in LIGHT should be the one labeled $\#00*$. By the naming function, this bucket $\#00*$ is mapped to $\#$. Likewise, the largest data key should be associated with leaf bucket $\#01*$, which is named to $\#0$. □

6.4 k-NN Queries

Given a data key δ and an integer k, the k-NN query returns the k-nearest data keys to δ. LIGHT supports k-NN query processing by a LIGHT lookup of δ, followed by a sequential leaf traversal. Specifically, after the bucket covering δ is located, a bidirectional leaf traversal is set off simultaneously toward the left and the right.

Without loss of generality, we focus on the traversal toward the right. The packet in the leaf traversal carries a parameter unf, which is an integer indicating how many keys still need to be found. It is initiated to k and at any time, $unf \leq k$. Suppose bucket b receives a k-NN query message of unf and data key δ. As described in Algorithm 6, it locally searches the nearest unf data keys to δ (line 1). Bucket b then returns the results directly to the query issuer (via a physical hop since the query issuer's address can be known from the packet header) (line 2). The query issuer will update the value of unf according to the current result set and notify bucket b of the new unf' (line 3). If the new

unf' is still bigger than 0, meaning that the current result set is not yet filled up, bucket b further forwards the query to its immediate right neighbor (lines 4-10). This is quite similar to the forwarding to β_i in the range query. A k-NN query traversing B buckets incurs at most $1.5B$ DHT-lookups since in the worst case 50 percent of DHT-lookups might fail (e.g., the hop from #0011 to #0100 always succeeds but the one from #0010 to #0011 can fail).

Algorithm 6. k-NN-forward(leaf bucket b, unf, δ)

```
1: $result \leftarrow b$.localsearch($\delta, unf$)
2: return $result$ to query initiator
3: $unf' \leftarrow$ update($unf$) {update $unf$ from query initiator}
4: if $unf' > 0$ then
5:    $\lambda \leftarrow b.leaflabel$
6:    $\beta \leftarrow f_{rn}(\lambda)$
7:    $nextbucket \leftarrow$ DHT-lookup($\beta$)
8:    if $nextbucket = NULL$ then {a failed DHT-lookup}
9:       $nextbucket \leftarrow$ DHT-lookup($f_n(\beta)$)
10:   k-NN-forward($nextbucket, unf', \delta$)
```

7 Experimental Results

This section presents the results of performance evaluation. We compare LIGHT with the state-of-the-art indexing schemes PHT [15] and DST [18] in terms of index maintenance costs and lookup/query performance.

7.1 Experiment Setup

We implemented LIGHT in Java. The total number of code lines is 2,200 (including LIGHT, DST, and PHT), which demonstrates the simplicity of developing an over-DHT indexing scheme. In the experiments, LIGHT, DST, and PHT were run over the Bamboo DHT [21], a ring-like DHT that has good robustness and is now widely deployed in the OpenDHT project [6]. Our whole system was deployed in a LAN environment consisting of more than 20 computers (or peers).[8]

Both real data and synthetic data were tested. For the real data, we used the DBLP data set, which contains the publications listed in the DBLP Computer Science Bibliography.[9] The author names were converted to a floating number in the domain of [0, 1] and used as the data keys. By filtering out duplicate author names, we obtained a DBLP data set containing approximately 250,000 distinct data keys (see Fig. 8 for the data distribution). We further divided the whole data set into five smaller data sets with 50,000 data keys each. The experiments were conducted against all the five small data sets; the average performance is reported here. To evaluate the scalability of the indexing schemes, we also used two synthetic data sets: *uniform* and *gaussian*, with sizes varying from 500,000 to 8,000,000. The data keys in the uniform data set were randomly generated in $[0, 1]$, while the data keys in the gaussian data set follow a gaussian distribution with a mean of $\frac{1}{2}$ and a standard deviation of $\frac{1}{6}$, which guarantees that about 97 percent of the keys will fall in $[0, 1]$ (see Fig. 8). For performance testing on the synthetic data, we repeated each experiment over 30 times and report the average results.

8. The performance measurements such as the number of DHT-lookups are independent of the network scale.

9. http://dblp.uni-trier.de/xml/.

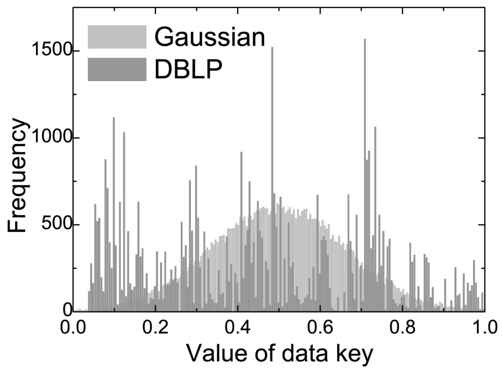


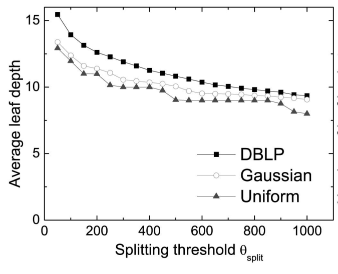
Fig. 8. Key distribution in DBLP and gaussian data set.

7.2 Structural Properties

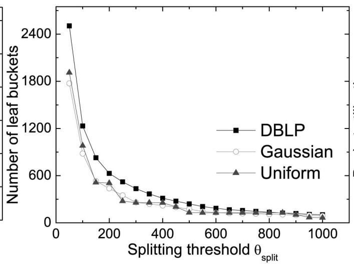
In this experiment, we examine the structural properties of the LIGHT index, including average leaf depth, number of leaf nodes, and *bucket utilization*. Bucket utilization is defined to be the ratio of the number of records stored in a leaf bucket to the bucket capacity θ_{split}. We measure these properties after we inserted 50,000 data keys into the LIGHT index. Fig. 9 shows the performance trends when θ_{split} is varied from 50 to 1,000. When θ_{split} grows large, both the average leaf depth and the number of leaf nodes decrease since a large θ results in leaves containing more keys and thus fewer leaf nodes. Comparing the three data sets under testing, DBLP has more and deeper leaf nodes. This is because the data distribution in DBLP is highly skewed, which makes the index tree very unbalanced. As shown in Fig. 10, most leaf nodes for the uniform data set have a depth of 13 or 14, whereas the depth of the leaf nodes for DBLP varies from 10 to 25. Fig. 9c shows the bucket utilization as a function of θ_{split}. As expected, the bucket utilization for the DBLP data set is lowest due to the skewness of data distribution. The bucket utilization for the synthetic data sets, especially the uniform data set, fluctuates as θ_{split} increases, owing to the characteristic of the space partition tree.

7.3 Lookup Performance

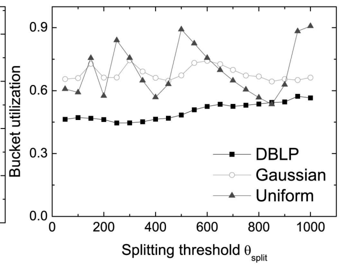
This experiment evaluates the efficiency of looking up a key in the index. We compare LIGHT with PHT with varying data set sizes. Note that the lookup operations in both LIGHT and PHT have a parameter D, the maximum leaf depth. To make a fair comparison, D is always set to the actual maximum tree depth for the data set under testing. The splitting threshold θ_{split} is fixed at the default value 100. For each experiment, we conduct 1,000 lookups for the keys uniformly distributed in $[0, 1]$ and record the average number of DHT-lookups per lookup operation. The results are shown in Fig. 11. In general, as expected, the number of DHT-lookups increases as the data set grows. For the DBLP and gaussian data sets, LIGHT outperforms PHT by 35 percent on average. For the uniform data set, the performance curve of PHT exhibits a zigzag shape (see Fig. 11c). This is because most leaf buckets reside in the deepest two levels of the tree (as seen in Fig. 10). As the data



(a)



(b)



(c)

Fig. 9. LIGHT structural properties with varied θ_{split}. (a) Average leaf depth. (b) Number of leaf nodes. (c) Bucket utilization.

set size is increased, the numbers of leaf buckets on these two levels are increased in turn, for which the binary search gets a fluctuating lookup performance.

7.4 Index Maintenance Performance

We now evaluate the index maintenance performance under data insertions and deletions. In the following, we first compare LIGHT with PHT for the leaf split cost (note that DST incurs no split cost [18]). We then compare the overall index maintenance performance among LIGHT, PHT, and DST.

7.4.1 Leaf Split Costs

In this set of experiments, we first measure the value of α for LIGHT, that is, the ratio of data records moved to remote peers during a leaf split. To evaluate it, we continuously insert data into the LIGHT index and record the average value of α for the leaf splits. As shown in Fig. 12, the average α remains almost constant under different data set sizes for the uniform and gaussian data sets. For the DBLP data set, the average α fluctuates a little bit when the data set size is smaller than 15,000 but becomes stable as the size of the data set increases. This is mainly because of the irregular distribution of DBLP data (Fig. 8). Fig. 12b shows the result as a function of θ_{split}. In all cases tested, the average α fairly approaches the value of 0.5, which is consistent with our previous analysis in Section 5.3.2.

Next we compare LIGHT with PHT for the leaf split performance. We continuously insert data into LIGHT and PHT and record the cumulative split costs. Recall that our leaf split involves data-movement costs and DHT-lookup costs (Section 5.3). We measure them separately in each experiment. Figs. 13a and 13b show the results for LIGHT and PHT indexing 50,000 DBLP data keys, with θ_{split} varied from 50 to 1,000. For both schemes, total data-movement costs slightly decrease as θ_{split} increases, while the number of DHT-lookups is inversely proportional to θ. The reason is that a larger θ_{split} results in fewer split operations. Comparing LIGHT with PHT, LIGHT improves PHT by 50 percent for data-movement costs and 75 percent for DHT-lookup costs, which conforms to our previous analysis. To further test the scalability, we conduct experiments on the synthetic data sets with varying data set sizes. From Figs. 13c and 13d, a similar performance improvement can be observed under different data set sizes for both the uniform and gaussian data sets.

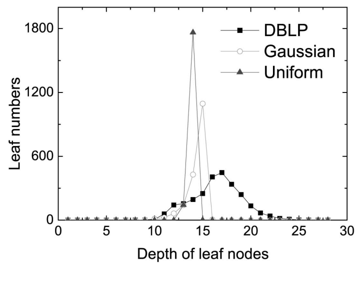


Fig. 10. Depth distribution.

7.4.2 Performance under Data Insertions

In this section, we evaluate performance under data insertions, which includes the costs incurred by both data insertion and leaf split. The same experimental settings are chosen as with the leaf split experiments. The results are shown in Figs. 14a and 14b. We can see that DST incurs a cost higher than LIGHT and PHT by an order of magnitude. This is because DST employs data replication. More specifically, each insertion in DST needs to look up all the ancestors of the leaf and insert the data into the unsaturated ancestors, which typically amplifies the insertion cost by a factor of D. Comparing LIGHT and PHT, LIGHT still outperforms PHT by about 40 percent for data-movement costs and 30 percent for DHT-lookup costs. This is because LIGHT achieves more efficient lookup and leaf split operations during the insertion process. From Figs. 14c and 14d, it is also interesting to observe that the relative performance of LIGHT, PHT, and DST is quite insensitive to the data distribution.

7.4.3 Performance under Data Deletions

We next study performance under data deletions. The experiments proceed in three phases: the growing phase, in which only data insertion is allowed; the steady phase, in which data insertions and deletions are randomly performed; and the shrinking phase, in which data is deleted from the P2P index until it is contracted into a single root. Recall that the leaf merge operation requires a threshold θ_{merge}. In the experiments, θ_{merge} is set to $0.5 \cdot \theta_{split}$ and $0.2 \cdot \theta_{split}$. Figs. 15a and 15b show the data-movement costs and DHT-lookup costs, respectively, for LIGHT and PHT under the DBLP data set, where the costs for DST are much higher and thus are not shown in the figures for clarity. In Fig. 15a, the data-movement costs remain relatively stable in the steady phase, implying that the split or merge

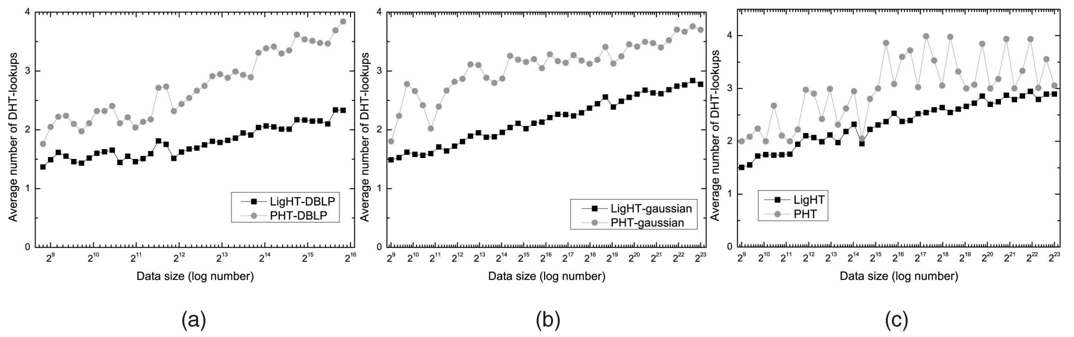


Fig. 11. LIGHT lookup performance on different data sets. (a) DBLP data set. (b) Gaussian data set. (c) Uniform data set.

operations rarely happen during this phase. This is because random insertions and deletions may cancel out each other's effects. Throughout the whole process, the cost of LIGHT remains half that of PHT, and they are both insensitive to the value of θ_{merge}. In contrast, the DHT-lookup costs in Fig. 15b are more sensitive to θ_{merge}—the smaller the θ_{merge}, the fewer DHT-lookups. This is because a large θ_{merge} leads to more DHT-lookups for probing the sibling's load. Similar performance results are also observed for the uniform and gaussian data sets in Figs. 15c and 15d, where θ_{merge} is fixed at $0.5 \cdot \theta_{split}$.

7.5 Range Query Performance

Finally, we evaluate the query processing performance for range queries. The evaluation is in terms of two aspects: time latency and bandwidth costs. The former is captured by the paralleled steps of DHT-lookups, while the latter is captured by the total number of DHT-lookups. Recall that we proposed two LIGHT range query algorithms, the basic one (in Section 6.1) and the one with lookahead (in Section 6.2). PHT also has two range query algorithms, denoted as PHT(sequential) [15] and PHT(parallel) [16], respectively. Thus, we compare these four range query algorithms together with DST.

Fig. 16 shows the range query performance on the DBLP data set. In Figs. 16a and 16b, the bandwidth costs generally go linearly with the data set size and the range span.[10] Among the five algorithms, LIGHT(basic) achieves the lowest bandwidth (though not quite visible in the figure), while PHT(sequential) requires a bandwidth slightly higher than LIGHT(basic). As discussed earlier, their performance nearly approaches the optimum, that is, the number of DHT-lookups equals the number of target leaf buckets. The bandwidth costs of PHT(parallel) and DST are twice that of LIGHT(basic) because they both incur internal node traversal when processing range queries. The bandwidth costs of LIGHT(lookahead) are approximately 50 percent higher than the optimal bandwidth, which again conforms to our previous complexity analysis. In terms of time latency, as shown in Figs. 16c and 16d, the two LIGHT algorithms substantially outperform the others. Without leveraging parallelism, PHT(sequential) incurs extremely high latency. Although parallelism is employed in PHT(parallel) and DST, they still suffer from data skewness for which the deepest leaf node dominates the whole query process.

10. For a queried range $[l, u)$, the range span is $u - l$.

For the scalability test on the synthetic uniform and gaussian data sets, a similar result is found in Fig. 17. The only exception here is that LIGHT(basic) incurs a slightly higher latency than DST because the skewness is much lower in the synthetic data and DST suits such unskewed distribution.

In summary, LIGHT(basic) outperforms all others in terms of bandwidth costs and achieves quite good time latency, just behind LIGHT(lookahead). LIGHT(lookahead) trades bandwidth for time latency, which makes its time latency the shortest. PHT(sequential) achieves quite efficient bandwidth costs but incurs extremely high latency. PHT(parallel) and DST both incur the highest bandwidth costs, but their latency is not yet the most efficient.

8 Enhancements

In this section, we further present two extensions to the LIGHT index, including how to index unbounded data domains and how to improve peer load balance.

8.1 Extensible Indexing

The basic LIGHT index deals with a bounded data domain (i.e., in the normalized [0, 1] space), which requires a priori knowledge of the indexed data. However, in many applications, such knowledge cannot be obtained in advance; and even more the data domain may change over time. For example, if we want to index the publication dates of MP3 files in a P2P file-sharing application, the data domain for publication dates is not fixed and evolves in $(-\infty, \infty)$. In this section, we propose *E-LIGHT*, an extensible LIGHT that supports data indexing of unbounded data domains.

Fig. 18 shows how the E-LIGHT indexes the domain $(-\infty, \infty)$. We introduce two *spine buckets*, that is, the

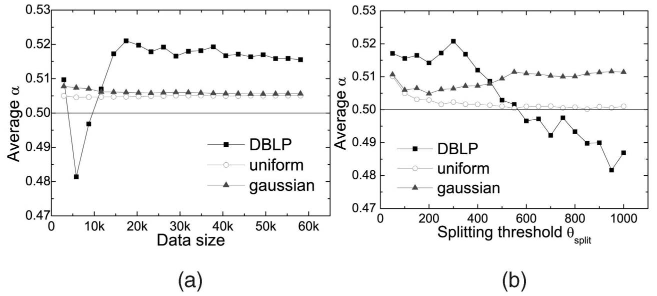


Fig. 12. LIGHT split costs (measured by α). (a) Varying data set size. (b) Varying θ_{split}.

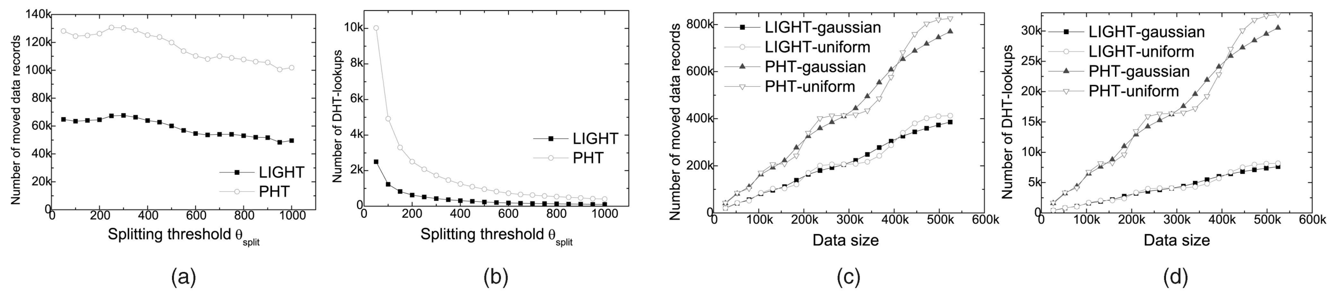


Fig. 13. Index maintenance costs of leaf split. (a) and (b) Varying θ_{split} on DBLP data set. (a) Data-movement costs and (b) DHT-lookup costs. (c) and (d) Scalability: varying data set size on synthetic data sets. (c) Data-movement costs and (d) DHT-lookup costs.

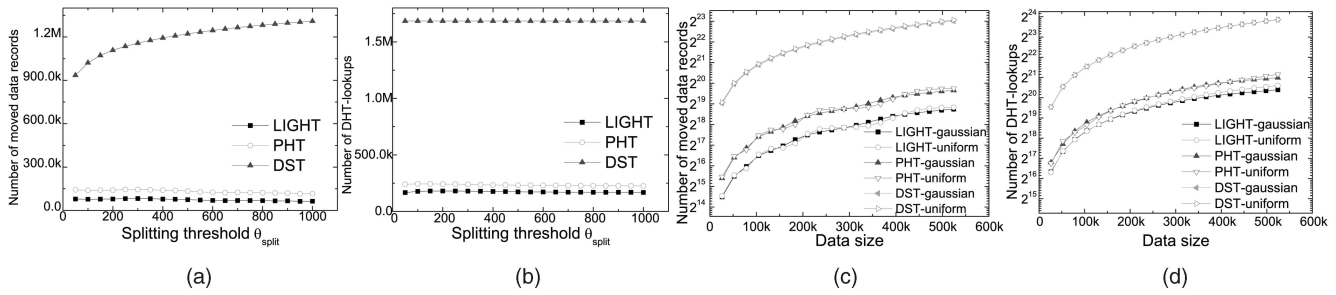


Fig. 14. Index maintenance costs under data insertions. (a) and (b) Varying θ_{split} on DBLP data set. (a) Data-movement costs and (b) DHT-lookup costs. (c) and (d) Scalability: varying data set size on synthetic data sets. (c) Data-movement costs and (d) DHT-lookup costs.

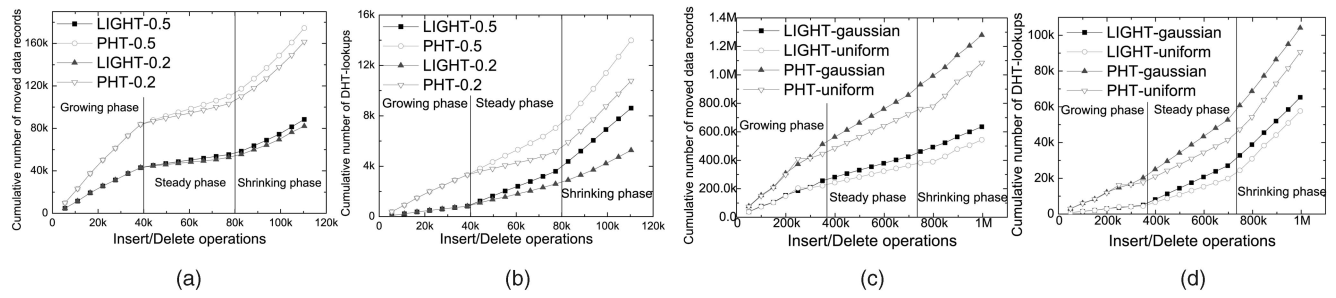


Fig. 15. Index maintenance costs under data deletions. (a) and (b) Performance on DBLP data set. (a) Data-movement costs and (b) DHT-lookup costs. (c) and (d) Performance on synthetic data set. (c) Data-movement costs and (d) DHT-lookup cost.

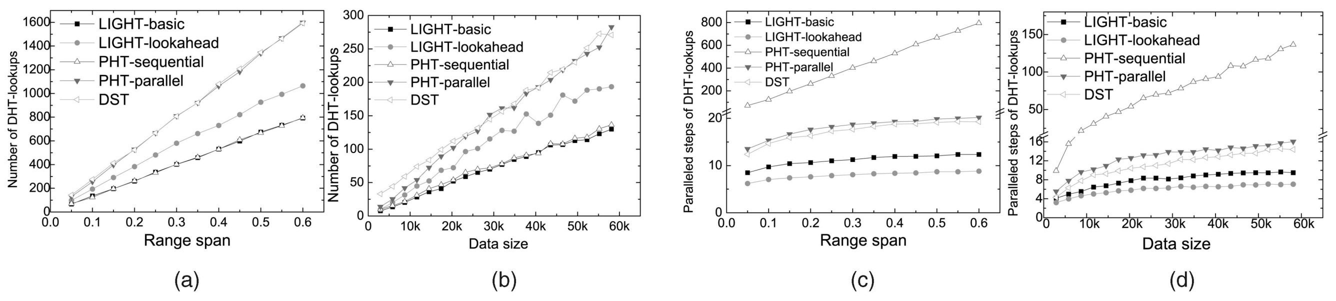


Fig. 16. Range query performance on DBLP data set. (a) and (b) Bandwidth costs. (a) Varying range span and (b) varying data size. (c) and (d) Time latency. (c) Varying range span and (d) varying data size.

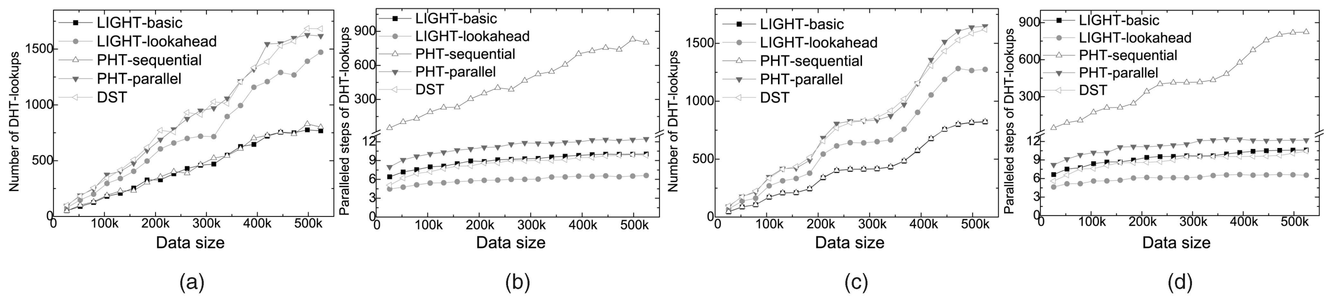


Fig. 17. Range query performance on synthetic data sets. (a) Bandwidth on gaussian data. (b) Latency on gaussian data. (c) Bandwidth on uniform data. (d) Latency on uniform data.

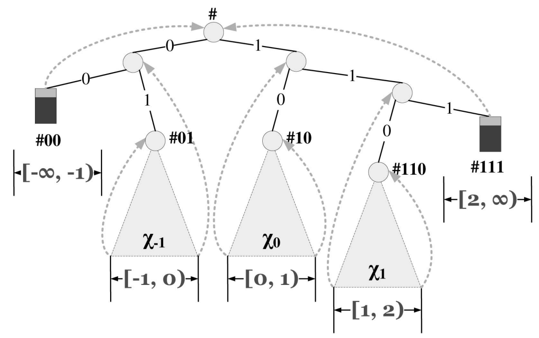


Fig. 18. Extensible LIGHT.

buckets whose labels are like $\#00*$ or $\#11*$. For example, in Fig. 18, the right spine bucket $\#111$ lies at the end of the right spine and indexes the space $[2, \infty)$. A spine bucket does not employ the binary partition strategy—when it splits, two subspaces can be $[2, 3)$ and $[3, \infty)$. Subspace $[2, 3)$ is then covered by bucket $\#1110$, which can subsequently grow into a conventional LIGHT, like $[1, 2)$ indexed by LIGHT χ_1. Essentially, each spine bucket acts as an extending point, and an E-LIGHT index consists of two spine buckets and a set of conventional LIGHTs.

In E-LIGHT, the naming function $f_n(\cdot)$ still applies, as depicted by the dotted arrows in Fig. 18. The only exception is that both spine buckets are named to the root $\#$, which may double the load of the DHT key $\#$. We thus impose the constraint: a spine bucket splits if it stores more than $\frac{\theta_{split}}{2}$ records. The algorithms for various complex queries in LIGHT can work in E-LIGHT without much modification. For example, given a data key $\delta \in (-\infty, \infty)$, we can easily figure out which LIGHT χ_i covers the key δ, and afterwards the LIGHT algorithm can be applied to χ_i.

8.2 Improvement of Peer Load Balance

In general, DHTs offer load balance quite efficiently, yet not that effectively. Specifically, if the *imbalance ratio* denotes the ratio of the heaviest load to the average load for the peers in the P2P network, DHTs only bound the imbalance ratio at $O(\log N)$ with high probability [5], [1]. This result is considerably large for large-scale P2P networks. In this section, we propose a *double-naming* strategy as an improvement for balancing peer load. The double-naming strategy naturally adapts the "power of two choices" paradigm [61] (PoTC) to LIGHT, which bounds the imbalance ratio at $O(\log \log N)$.

The basic idea behind the double-naming strategy is simple. Previously in LIGHT, each leaf bucket λ had one name, $f_n(\lambda)$. Now, the double-naming strategy adds another name, that is, λ itself. Thus, for each bucket, there are two distinct names, λ and $f_n(\lambda)$ (note that $f_n(\lambda) \neq \lambda$), which implies that one bucket can have two choices of underlying peers to store it. Between these two candidates, it picks the one with lighter load to actually store the bucket λ. Since the load of the peer may change over time, the bucket periodically checks these two peers, and accordingly adjusts its storage location. Unlike PoTC's other adaptations that come with double hashes within DHTs [62], the double-naming strategy is completely independent of DHTs and can be seamlessly incorporated into LIGHT.

The adaptability comes with prices—to locate the bucket λ, now two (rather than one) DHT-lookups are needed. For more efficiency, one possible solution is to trade the adaptability. Specifically, a physical link (at the IP level) is maintained between each pair of two candidate peers which, although it incurs modification of underlying DHTs, accelerates the indirection of the failed DHT-lookup and the periodical reassessment of bucket location. So, now it consumes one DHT-lookup and a possible physical hop to locate a leaf bucket; this extra hop is trivial, since a typical DHT-lookup incurs $O(\log N)$ physical hops. By this means, various LIGHT algorithms still apply in the double-naming LIGHT, without loss of efficiency.

9 Conclusion

This paper proposed LIGHT, a LIGhtweight Hash Tree, for efficient data indexing over DHTs. LIGHT differs from PHT, a representative over-DHT indexing scheme, in the following aspects:

- Both PHT and LIGHT are based on the idea of space partitioning. While PHT maps its index structure into DHT in a straightforward manner, LIGHT leverages a clever naming function, which significantly lowers the maintenance cost and improves the DHT-lookup performance.
- LIGHT employs local tree summarization to provide each bucket a local view. This local view is essentially helpful for distributed query processing, but unlike PHT's sequential leaf link, requires no extra maintenance cost.
- In PHT, all leaf nodes and internal nodes are mapped to the DHT space, whereas only leaf nodes are mapped in LIGHT. The processing of range queries in PHT has to go through all internal nodes of the subtree in addition to the leaf nodes in the queried range, which at least doubles the search cost.
- Thanks to the novel naming function, one can easily determine the leftmost/rightmost leaf node under a subtree in O(1) lookup. As such, min/max queries can be efficiently supported in LIGHT.
- LIGHT can be extended to index unbounded data domains and naturally accommodate a double-naming strategy to improve peer load balance. As a comparison, PHT (and other existing over-DHT schemes) only supports data indexing of bounded domains and achieves better load balance by modifying DHTs.

Experimental results show that in comparison with the state-of-the-art indexing techniques PHT and DST, LIGHT saves 50-75 percent of index maintenance cost and supports more efficient lookup operations. Moreover, LIGHT has a much better query performance in terms of both bandwidth consumption and response time. As an over-DHT scheme, LIGHT is adaptable to generic DHTs and can be easily implemented and deployed in any DHT-based P2P system.

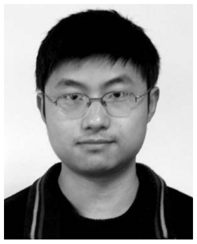
ACKNOWLEDGMENTS

The authors would like to thank the anonymous reviewers. This work was supported by the National Natural Science Foundation of China under Grant Nos. 60573183, 90612007, and 60873070, and Shanghai Leading Academic Discipline Project No. B114. Shuigeng Zhou's work was also supported by K.C. Wong Education Foundation-HKBU. Jianliang Xu's work was supported by grants from the Research Grants Council, Hong Kong SAR, China (Project Nos. HKBU211307 and HKBU210808).

REFERENCES

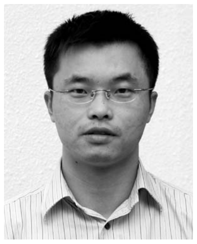
[1] I. Stoica, R. Morris, D.R. Karger, M.F. Kaashoek, and H. Balakrishnan, "Chord: A Scalable Peer-to-Peer Lookup Service for Internet Applications," *Proc. 2003 Conf. Applications, Technologies, Architectures, and Protocols for Computer Comm. (SIGCOMM)*, pp. 149-160, 2001.
[2] S. Ratnasamy, P. Francis, M. Handley, R.M. Karp, and S. Shenker, "A Scalable Content-Addressable Network," *Proc. 2001 Conf. Applications, Technologies, Architectures, and Protocols for Computer Comm. (SIGCOMM)*, pp. 161-172, 2001.
[3] A.I.T. Rowstron and P. Druschel, "Pastry: Scalable, Decentralized Object Location, and Routing for Large-Scale Peer-to-Peer Systems," *Proc. Middleware*, pp. 329-350, 2001.
[4] B.Y. Zhao, J. Kubiatowicz, and A.D. Joseph, "Tapestry: A Fault-Tolerant Wide Area Application Infrastructure," *Computer Comm. Rev.*, vol. 32, no. 1, p. 81, 2002.
[5] D.R. Karger, E. Lehman, F.T. Leighton, R. Panigrahy, M.S. Levine, and D. Lewin, "Consistent Hashing and Random Trees: Distributed Caching Protocols for Relieving Hot Spots on the World Wide Web," *Proc. Symp. Theory of Computing (STOC)*, pp. 654-663, 1997.
[6] S.C. Rhea, B. Godfrey, B. Karp, J. Kubiatowicz, S. Ratnasamy, S. Shenker, I. Stoica, and H. Yu, "OpenDHT: A Public DHT Service and Its Uses," *Proc. 2005 Conf. Applications, Technologies, Architectures, and Protocols for Computer Comm. (SIGCOMM)*, pp. 73-84, 2005.
[7] P. Maymounkov and D. Mazières, "Kademlia: A Peer-to-Peer Information System Based on the XOR Metric," *Proc. Int'l Workshop Peer-to-Peer Systems (IPTPS)*, pp. 53-65, 2002.
[8] http://en.wikipedia.org/wiki/kademlia, 2009.
[9] A.I.T. Rowstron and P. Druschel, "Storage Management and Caching in Past, a Large-Scale, Persistent Peer-to-Peer Storage Utility," *Proc. Symp. Operating Systems Principles (SOSP)*, pp. 188-201, 2001.
[10] J. Kubiatowicz, D. Bindel, Y. Chen, S.E. Czerwinski, P.R. Eaton, D. Geels, R. Gummadi, S.C. Rhea, H. Weatherspoon, W. Weimer, C. Wells, and B.Y. Zhao, "Oceanstore: An Architecture for Global-Scale Persistent Storage," *Proc. Architectural Support for Programming Languages and Operating Systems (ASPLOS)*, pp. 190-201, 2000.
[11] F. Dabek, M.F. Kaashoek, D.R. Karger, R. Morris, and I. Stoica, "Wide Area Cooperative Storage with CFS," *Proc. Symp. Operating Systems Principles (SOSP)*, pp. 202-215, 2001.
[12] M.J. Freedman, E. Freudenthal, and D. Mazières, "Democratizing Content Publication with Coral," *Proc. Networked Systems Design and Implementation (NSDI)*, pp. 239-252, 2004.
[13] I. Stoica, D. Adkins, S. Zhuang, S. Shenker, and S. Surana, "Internet Indirection Infrastructure," *Proc. 2002 Conf. Applications, Technologies, Architectures, and Protocols for Computer Comm. (SIGCOMM)*, pp. 73-86, 2002.
[14] M.J. Freedman, K. Lakshminarayanan, and D. Mazières, "Oasis: Anycast for Any Service," *Proc. Networked Systems Design and Implementation (NSDI)*, 2006.
[15] S. Ramabhadran, S. Ratnasamy, J.M. Hellerstein, and S. Shenker, "Brief Announcement: Prefix Hash Tree," *Proc. Principles of Distributed Computing (PODC)*, p. 368, 2004.
[16] Y. Chawathe, S. Ramabhadran, S. Ratnasamy, A. LaMarca, S. Shenker, and J.M. Hellerstein, "A Case Study in Building Layered DHT Applications," *Proc. 2005 Conf. Applications, Technologies, Architectures, and Protocols for Computer Comm. (SIGCOMM)*, pp. 97-108, 2005.
[17] J. Gao and P. Steenkiste, "An Adaptive Protocol for Efficient Support of Range Queries in DHT-Based Systems," *Proc. IEEE Int'l Conf. Network Protocols (ICNP)*, pp. 239-250, 2004.
[18] C. Zheng, G. Shen, S. Li, and S. Shenker, "Distributed Segment Tree: Support of Range Query Cover Query over DHT," *Proc. Fifth Int'l Workshop Peer-to-Peer Systems (IPTPS)*, Feb. 2006.
[19] B. Yang and H. Garcia-Molina, "Comparing Hybrid Peer-to-Peer Systems," *Proc. Very Large Data Bases (VLDB)*, pp. 561-570, 2001.
[20] S. Saroiu, P. Gummadi, and S. Gribble, "A Measurement Study of Peer-to-Peer File Sharing Systems," www.citeseer.ist.psu.edu/saroiu02measurement.html, 2002.
[21] S.C. Rhea, D. Geels, T. Roscoe, and J. Kubiatowicz, "Handling Churn in a DHT," *Proc. USENIX Ann. Technical Conf. (ATC)*, pp. 127-140, 2004.
[22] C.G. Plaxton, R. Rajaraman, and A.W. Richa, "Accessing Nearby Copies of Replicated Objects in a Distributed Environment," *Proc. Symp. Parallel Algorithms and Architectures (SPAA)*, pp. 311-320, 1997.
[23] W.G. Bridges and S. Toueg, "On the Impossibility of Directed Moore Graphs," *J. Combinatorial Theory, Series B*, vol. 29, no. 3, pp. 339-341, 1980.
[24] P. Fraigniaud and P. Gauron, "Brief Announcement: An Overview of the Content-Addressable Network D2B," *Proc. Principles of Distributed Computing (PODC)*, p. 151, 2003.
[25] D. Loguinov, A. Kumar, V. Rai, and S. Ganesh, "Graph-Theoretic Analysis of Structured Peer-to-Peer Systems: Routing Distances and Fault Resilience," *Proc. 2003 Conf. Applications, Technologies, Architectures, and Protocols for Computer Comm. (SIGCOMM)*, pp. 395-406, 2003.
[26] D. Malkhi, M. Naor, and D. Ratajczak, "Viceroy: A Scalable and Dynamic Emulation of the Butterfly," *Proc. Principles of Distributed Computing (PODC)*, pp. 183-192, 2002.
[27] D. Li, X. Lu, and J. Wu, "Fissione: A Scalable Constant Degree and Low Congestion DHT Scheme Based on Kautz Graphs," *Proc. IEEE Int'l Conf. Computer Comm. (INFOCOM)*, pp. 1677-1688, 2005.
[28] J. Liang and K. Nahrstedt, "Randpeer: Membership Management for QoS Sensitive Peer-to-Peer Applications," *Proc. IEEE Int'l Conf. Computer Comm. (INFOCOM)*, 2006.
[29] O.D. Sahin, A. Gulbeden, F. Emekçi, D. Agrawal, and A.E. Abbadi, "PRISM: Indexing Multi-Dimensional Data in P2P Networks Using Reference Vectors," *Proc. 13th Ann. ACM Int'l Conf. Multimedia (MM)*, pp. 946-955, 2005.
[30] J. Gao and P. Steenkiste, "Efficient Support for Similarity Searches in DHT-Based Peer-to-Peer Systems," *Proc. Int'l Conf. Comm. (ICC)*, pp. 1867-1874, 2007.
[31] L. Chen, K.S. Candan, J. Tatemura, D. Agrawal, and D. Cavendish, "On Overlay Schemes to Support Point-in-Range Queries for Scalable Grid Resource Discovery," *Proc. IEEE Int'l Conf. Peer-to-Peer Computing (P2P)*, pp. 23-30, 2005.
[32] E. Tanin, A. Harwood, and H. Samet, "Using a Distributed Quadtree Index in Peer-to-Peer Networks," *Very Large Data Bases J.*, vol. 16, no. 2, pp. 165-178, 2007.
[33] R. Huebsch, J.M. Hellerstein, N. Lanham, B.T. Loo, S. Shenker, and I. Stoica, "Querying the Internet with Pier," *Proc. Very Large Data Bases (VLDB)*, pp. 321-332, 2003.
[34] S. Idreos, C. Tryfonopoulos, and M. Koubarakis, "Distributed Evaluation of Continuous Equi-Join Queries over Large Structured Overlay Networks," *Proc. Int'l Conf. Data Eng. (ICDE)*, p. 43-54, 2006.
[35] S. Idreos, E. Liarou, and M. Koubarakis, "Continuous Multi-Way Joins over Distributed Hash Tables," *Proc. Extending Data Base Technology (EDBT)*, 2008.
[36] P. Reynolds and A. Vahdat, "Efficient Peer-to-Peer Keyword Searching," *Proc. Middleware*, pp. 21-40, 2003.
[37] C. Tang, S. Dwarkadas, and Z. Xu, "On Scaling Latent Semantic Indexing for Large Peer-to-Peer Systems," *Proc. 27th Ann. Int'l ACM SIGIR Conf. Research and Development in Information Retrieval*, pp. 112-121, 2004.
[38] C. Tang and S. Dwarkadas, "Hybrid Global-Local Indexing for Efficient Peer-to-Peer Information Retrieval," *Proc. Networked Systems Design and Implementation (NSDI)*, pp. 211-224, 2004.
[39] M. Cai and M.R. Frank, "RDFpeers: A Scalable Distributed RDF Repository Based on a Structured Peer-to-Peer Network," *Proc. World Wide Web (WWW)*, pp. 650-657, 2004.
[40] L. Galanis, Y. Wang, S.R. Jeffery, and D.J. DeWitt, "Locating Data Sources in Large Distributed Systems," *Proc. Very Large Data Bases (VLDB)*, pp. 874-885, 2003.

[41] A. Andrzejak and Z. Xu, "Scalable, Efficient Range Queries for Grid Information Services," *Proc. IEEE Int'l Conf. Peer-to-Peer Computing (P2P),* pp. 33-40, 2002.
[42] C. Schmidt and M. Parashar, "Flexible Information Discovery in Decentralized Distributed Systems," *Proc. High Performance Distributed Computing (HPDC),* pp. 226-235, 2003.
[43] A. Datta, M. Hauswirth, R. John, R. Schmidt, and K. Aberer, "Range Queries in Trie-Structured Overlays," *Proc. IEEE Int'l Conf. Peer-to-Peer Computing (P2P),* pp. 57-66, 2005.
[44] D. Li, X. Lu, B. Wang, J. Su, J. Cao, K.C.C. Chan, and H.V. Leong, "Delay-Bounded Range Queries in DHT-Based Peer-to-Peer Systems," *Proc. Int'l Conf. Distributed Computing Systems (ICDCS),* p. 64-71, 2006.
[45] D. Li, J. Cao, X. Lu, and K.C.C. Chan, "Efficient Range Query Processing in Peer-to-Peer Systems," *IEEE Trans. Knowledge and Data Eng.,* vol. 21, no. 1, pp. 78-91, Jan. 2009.
[46] A. Gupta, D. Agrawal, and A.E. Abbadi, "Approximate Range Selection Queries in Peer-to-Peer Systems," *Proc. Conf. Innovative Data Systems Research (CIDR),* 2003.
[47] M. Bawa, T. Condie, and P. Ganesan, "Lsh Forest: Self-Tuning Indexes for Similarity Search," *Proc. World Wide Web (WWW),* pp. 651-660, 2005.
[48] Y.-J. Joung, C.-T. Fang, and L.-W. Yang, "Keyword Search in DHT-Based Peer-to-Peer Networks," *Proc. Int'l Conf. Distributed Computing Systems (ICDCS),* pp. 339-348, 2005.
[49] Y.-J. Joung and L.-W. Yang, "KISS: A Simple Prefix Search Scheme in P2P Networks," *Proc. Workshop Web and Databases (WebDB),* 2006.
[50] D. Han, T. Shen, S. Meng, and Y. Yu, "Cuckoo Ring: Balancing Workload for Locality Sensitive Hash," *Proc. IEEE Int'l Conf. Peer-to-Peer Computing (P2P),* pp. 49-56, 2006.
[51] J. Aspnes and G. Shah, "Skip Graphs," *Proc. Symp. Discrete Algorithms (SODA),* pp. 384-393, 2003.
[52] A. Crainiceanu, P. Linga, J. Gehrke, and J. Shanmugasundaram, "Querying Peer-to-Peer Networks Using P-Trees," *Proc. Workshop Web and Databases (WebDB),* pp. 25-30, 2004.
[53] A. Crainiceanu, P. Linga, A. Machanavajjhala, J. Gehrke, and J. Shanmugasundaram, "P-Ring: An Efficient and Robust P2P Range Index Structure," *Proc. ACM SIGMOD,* pp. 223-234, 2007.
[54] H.V. Jagadish, B.C. Ooi, and Q.H. Vu, "Baton: A Balanced Tree Structure for Peer-to-Peer Networks," *Proc. Very Large Data Bases (VLDB),* pp. 661-672, 2005.
[55] H.V. Jagadish, B.C. Ooi, Q.H. Vu, R. Zhang, and A. Zhou, "VBI-Tree: A Peer-to-Peer Framework for Supporting Multi-Dimensional Indexing Schemes," *Proc. Int'l Conf. Data Eng. (ICDE),* p. 34, 2006.
[56] C. du Mouza, W. Litwin, and P. Rigaux, "SD-Rtree: A Scalable Distributed Rtree," *Proc. Int'l Conf. Data Eng. (ICDE),* pp. 296-305, 2007.
[57] A.R. Bharambe, M. Agrawal, and S. Seshan, "Mercury: Supporting Scalable Multi-Attribute Range Queries," *Proc. 2004 Conf. Applications, Technologies, Architectures, and Protocols for Computer Comm. and ACM SIGCOMM Computer Comm. Rev.,* pp. 353-366, 2004.
[58] P. Ganesan, M. Bawa, and H. Garcia-Molina, "Online Balancing of Range-Partitioned Data with Applications to Peer-to-Peer Systems," *Proc. Very Large Data Bases (VLDB),* pp. 444-455, 2004.
[59] D.R. Karger and M. Ruhl, "Simple Efficient Load Balancing Algorithms for Peer-to-Peer Systems," *Proc. Symp. Parallel Algorithms and Architectures (SPAA),* pp. 36-43, 2004.
[60] P. Yalagandu and J. Browne, "Solving Range Queries in a Distributed System," Technical Report TR-04-18, 04-18, Dept. of Computer Sciences, Univ. of Texas at Austin, 2003.
[61] M. Mitzenmacher, "The Power of Two Choices in Randomized Load Balancing," "*IEEE Trans. Parallel and Distributed Systems,* vol. 12, no. 10, pp. 1094-1104, Oct. 2001.
[62] J.W. Byers, J. Considine, and M. Mitzenmacher, "Simple Load Balancing for Distributed Hash Tables," *Proc. Int'l Workshop Peer-to-Peer Systems (IPTPS),* pp. 80-87, 2003.



Yuzhe Tang received the BSc degree in computer science and engineering from Fudan University, Shanghai, China, in 2006. He is currently working toward the MSc degree in the School of Computer Science, Fudan University. His research interests include peer-to-peer networks, data management, and distributed computing systems.

Shuigeng Zhou received the bachelor's degree from Huazhong University of Science and Technology (HUST) in 1988, the master's degree from the University of Electronic Science and Technology of China (UESTC) in 1991, and the PhD degree in computer science from Fudan University in 2000. He served in at the Shanghai Academy of Spaceflight Technology from 1991 to 1997 as an engineer and as a senior engineer (since August 1995). He was a postdoctoral researcher in the State Key Lab of Software Engineering, Wuhan University, from 2000 to 2002. He is now a professor in the School of Computer Science, Fudan University, Shanghai, China. His research interests include data management in P2P and sensor networks, data mining, information retrieval, and complex networks. He has published more than 100 papers in domestic and international journals (including *IEEE TKDE*, *IEEE TPDS*, *DKE*, *PRE*, *EPL*, and *EPJB*) and conferences (including ICDE, SIGKDD, and SIGIR). Currently, he is a member of the IEEE, the ACM, and the IEICE.



Jianliang Xu received the BEng degree in computer science and engineering from Zhejiang University, Hangzhou, China, in 1998, and the PhD degree in computer science from Hong Kong University of Science and Technology, in 2002. He is an associate professor in the Department of Computer Science, Hong Kong Baptist University. He was a visiting scholar in the Department of Computer Science and Engineering, Pennsylvania State University, University Park. His research interests include data management, mobile/pervasive computing, wireless sensor networks, and distributed systems. He has published more than 70 technical papers in these areas, most of which appeared in prestigious journals and conference proceedings, including ACM SIGMOD, IEEE ICDE, IEEE INFOCOM, *TKDE*, *TPDS*, and *VLDBJ*. He is an editor of a book entitled *Web Content Delivery*, published by Springer, and a coguest editor of the *International Journal of Grid Computing: Theory, Methods and Applications* (Elsevier) for a special issue on scalable information systems. He serves as a vice chairman of the ACM Hong Kong Chapter. He is a senior member of the IEEE.