Scalable Locality-Sensitive Hashing for Similarity Search in High-Dimensional, Large-Scale Multimedia Datasets

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Abstract—Similarity search is critical for many database applications, including the increasingly popular online services for Content-Based Multimedia Retrieval (CBMR). These services, which include image search engines, must handle an overwhelming volume of data, while keeping low response times. Thus, scalability is imperative for similarity search in Web-scale applications, but most existing methods are sequential and target shared-memory machines. Here we address these issues with a distributed, efficient, and scalable index based on Locality-Sensitive Hashing (LSH). LSH is one of the most efficient and popular techniques for similarity search, but its poor referential locality properties has made its implementation a challenging problem. Our solution is based on a widely asynchronous dataflow parallelization with a number of optimizations that include a hierarchical parallelization to decouple indexing and data storage, locality-aware data partition strategies to reduce message passing, and multi-probing to limit memory usage. The proposed parallelization attained an efficiency of 90% in a distributed system with about 800 CPU cores. In particular, the original locality-aware data partition reduced the number of messages exchanged by two orders of magnitude larger than datasets that previous LSH parallelizations could handle.

Keywords: Descriptor indexing; Information retrieval; Locality-Sensitive Hashing.

I. INTRODUCTION

Similarity search consists in finding in a reference dataset the most similar objects to a query object. Multimedia retrieval applications typically represent objects (images, videos, songs, etc) as high-dimensional feature vectors. In this context, similarity search is abstracted as finding the vectors in the dataset which are closest to a query vector, using a given distance (often Euclidean). Similarity search is a core operation for content-based multimedia retrieval (CBMR) applications such as image search engines, real-time song identification, tagging of photos in social networks, etc. [1], [2], [3], [4], [5], [6] Query processing in these applications may consist of several complex stages, but still similarity search will be one of the most critical and costly steps.

The success of current Web-scale CBMR applications, such as image search engines, depends on their ability to efficiently handle very large and increasing volumes of data, while keeping low the response times as observed by users. Although the amount of data to be indexed by these applications exceeds the capabilities of commodity machines, most of the state-of-the-art indexing methods have been designed for sequential execution in shared-memory systems.

In this work, we address the challenges of efficiently performing similarity search for large-scale CBMR services on distributed environment. We design and implement a distributed, efficient, and scalable similarity search index based on Locality-Sensitive Hashing (LSH), one of the most efficient and popular approaches for similarity search [7]. It relies on the use of a family of locality-preserving hash function, creating several hash tables that hash together similar objects with high probability. During search phase, the hash tables can be queried to retrieve a relatively small set of objects which are good candidates to be the closest to the query object. The distance is then computed to those candidates and the best are returned as a (very good) approximate solution to the similarity search.

LSH indexing has been shown to be a very challenging algorithm for parallelization in distributed memory machines because of the lack of referential locality induced by the “curse of dimensionality”. It is very difficult to partition the dataset for parallel execution without incurring in excessive communication during the search phase. Additionally, on sequential LSH implementations, efficiency is based upon the use of a large number of hash tables, each of them indexing the entire dataset. For shared-memory systems with uniform access costs, LSH hash tables will typically store references for the actual data objects, in order to avoid replicating the dataset. This is, however, an issue distributed environments: since replicating the dataset for each table is not feasible, once the references are retrieved the actual data must be accessed and the “curse of dimensionality” makes it difficult to arrange them in order to warrant good locality. If care is not taken, this phase will drown the system with...
messages, ruining performance.

The challenges of parallelizing LSH are addressed in our work with: (i) a decomposition of the method into a dataflow of computing stages, such that the hash buckets storing references to the dataset objects and the data objects are stored into different application stages in order to avoid data replication; (ii) a hierarchical parallelization in which stateful stages of the application are designed as multi-threaded processes that take advantage of multiple CPU cores in a node. It results into a smaller number of data partitions (one per node instead of one per CPU core), and an improved scalability because of the reduced communication; (iii) a study of multiple data partition strategies to effectively distribute state, which shows that adequate locality-aware data partition may lead to substantial reduction in communication; (iv) a widely asynchronous design that allows for the algorithm to overlap communication and computation; and, (v) a multi-probe LSH that allows for a smaller number of hash tables to be used, while multiple buckets are visited in each table to achieve the required search quality.

All these propositions have been thoroughly evaluated using what is to the best of our knowledge the largest publicly available dataset for CBMR applications. This dataset contains 1 billion 128-dimensional SIFT (Scale-Invariant Feature Transform) feature vectors extracted from images collected in the Web. This dataset is about two orders of magnitude larger than the largest dataset processed using LSH indexing methods prior to our work. Additionally, our parallelization has attained about 90% of efficiency with the use of 801 CPU cores/51 nodes. The performance evaluation of the distributed multi-probe version of LSH attains sublinear increasing in the communication as the number of probes per table grows, resulting into a surprisingly good trade-off between performance and search quality.

The rest of this paper is organized as follows: Section II introduces the similarity search (nearest neighbors) problem in high-dimensional spaces and presents some of the most popular indexing methods; Section III details the main concepts used by the LSH indexing as well as recent improvements in the basic LSH; Our distributed memory parallelization of the LSH indexing is discussed in Section IV and, the experimental results and conclusions are presented, respectively, in Sections V and VI.

II. BACKGROUND

A. Nearest Neighbors Search

The nearest neighbors (NN) search problem has received increasing attention in the last decades. Several efforts have focused on the development of data structures, including kdtree [9], k-means tree [10], cover trees [11], and others that provide a locality-aware partition of the input data, allowing to prune the search space in a NN search. However, this ability to find the relevant partitions in space quickly degrades as data dimensionality increases. This phenomenon is the well-known “curse of dimensionality”, which expresses the difficult in efficiently partitioning the data or the space as dimensionality grows [1], [2].

The approximate nearest neighbors (ANN) search was proposed to improve the scalability of NN search in high-dimensional spaces for applications where exact answers can be traded off for speed. A number of techniques and algorithms for ANN search in high-dimensional spaces have been recently proposed [13], [14], [5], [3]. FLANN [14] builds a framework that dynamically selects the best index, among algorithms such as randomized KD-trees [15], hierarchical k-means [16], and LSH [13], for a given dataset. Multicurves [5] performs multiple projections of subsets of the data objects dimensions to an 1-dimension space using space-filling curves, and builds a sorted list for each projection. Its search phase executes the same projections using the query object, and uses them to retrieve the nearest points in the 1-dimension sorted lists as the candidates for nearest neighbors. Finally, a ranking phase is executed to retrieve the nearest elements from the set of candidates. The Product Quantization based ANN search [3] is another successful approach, which decomposes the space into a Cartesian product of subspaces of lower dimensionality to further quantize subspaces. The vector created from the quantized subspaces is then used to estimate Euclidean distances.

Indexes based on locality sensitive hashing (LSH) [13] are very popular and well recognized as one of the most competitive techniques for similarity search in high-dimensional spaces. We explain those techniques in more detail in Section III.

B. Parallel and Distributed ANN Search

The ANN requirements for online CBMR systems are stringent and include searching in very large datasets that grow fast as time passes, achieving high throughput, and providing low response times to end-users. These demands have motivated the development of ANN indexing methods that make use of high performance techniques [17], [18], [19], [20], [6], [21], [22].

The MapReduce based parallelizations of LSH [17], [18] are the closest related works to ours. In the work of Stupar et. al [17] the MapReduce formulation of LSH has: 1) a map phase that independently visits buckets to which a query object is hashed to generate a per bucket nearest neighbors set; and 2) a reduce phase to aggregate results from all buckets visited during a query computation. This LSH implementation stores the buckets of points in a distributed file system (HDFS) using a single file per bucket value. As reported by the authors, combinations of LSH parameters may create a very large number of files (buckets) and decreases the overall system performance. In addition, this implementation stores data objects content in the bucket (files) for each hash table used, instead of the object identifier (pointer)
as in the original algorithm. As a consequence, the entire dataset is replicated for each of the hash table used by LSH. This level of data replication is prohibitive for large-scale datasets, since LSH may require the use of several tables. Also, the high latency of data accesses makes this solution impractical for online applications due to the high query-processing times.

Bahmani et al. [13] implemented another MapReduce-based variant of the classic LSH algorithm that is referred to as Layered LSH. They have implemented two versions of LSH using: 1) Hadoop for file system based data storage and 2) Active DHT for in-memory data storage. They proposed theoretical bounds for network traffic assuming that a single LSH hash table is used. This assumption greatly simplifies the analysis and implementation of the algorithm, but it may not be realistic because LSH typically achieves higher efficiency with the use of several hash tables [13]. If multiple hash tables are used, the theoretical propositions are not valid because the same data object is indexed by multiple buckets from different hash tables and the data partition would not be simple as in the case of a single table. Neither of the MapReduce based parallelizations of LSH [17], [18] solves the challenging problem of building a large-scale LSH-based searching index that minimizes communication and avoids data replication, while preserving the behavior of the sequential algorithm and providing low query response-times as required in several online multimedia services. As presented in Section IV, the parallelization strategy we propose in the paper addresses all these limitations.

III. LOCALITY-SENSITIVE HASHING (LSH)

LSH employs locality-sensitive hash functions to assign objects to buckets via quantization, such that similar objects are assigned together with high probability. Indexing the dataset consists in hashing its objects to the buckets. The ANN search can then be carried out by (1) finding the buckets to which a query \( q \) is hashed and selecting the objects in those buckets as candidates, and (2) ranking candidates according to their actual distance to the query (See Figure 1).

A. Locality-Sensitive Hashing Functions

LSH relies on the existence on a family of locality-sensitive hashing functions, from which individual hashing functions can be sampled randomly. The special property of the LSH function family that makes it useful for ANN search is a guarantee that, as we keep sampling functions, they will tend to hash together objects that are close, and hash apart objects that are distant.

More formally, assuming that \( S \) is the domain of the objects, \( U \) is the domain of the hash keys, and \( D \) is a distance function between objects:

**Definition 1:** A function family \( H = \{ h : S \rightarrow U \} \) is called \((r, cr, p_1, p_2)\)-sensitive for \( D \) if, for any \( p, q \in S \):

- If \( D(p, q) \leq r \) then \( Pr_{H}[h(q) = h(p)] \geq p_1 \),
- If \( D(p, q) > cr \) then \( Pr_{H}[h(q) = h(p)] \leq p_2 \).

In order to be useful for ANN search, we must have \( c > 1 \) and \( p_1 > p_2 \), which guarantees that objects within distance \( r \) of the query \( q \) have higher probability \( (p_1) \) of colliding with \( q \) than those at distance greater than \( cr \) \( (p_2) \).

The existence of locality-sensitive function families was proved by Indyk et al. [23], in the seminal paper that also introduced LSH indexing. Since then, other families have been introduced (each family works for a specific combination of data domain and distance function). Of particular interest for practical applications are the \( p \)-stable family [24] that exploits the stability of the Gaussian distribution under the \( \ell_2 \)-norm to hash data in the Euclidean spaces.

An individual hash function from the \( p \)-stable family is defined as:

\[
h_{a,b}(v) = \left[ \frac{a \cdot v + b}{w} \right]
\]

where \( a \in \mathbb{R}^d \) is a random Gaussian vector sampled from \( \mathcal{N}(0, I) \), and \( b \) is a random offset scalar sampled from \( \text{unif}(0, w) \). Sampling the values of \( a \) and \( b \) from their distributions consists, effectively, in sampling an individual hash function from the family. The parameter \( w \) is fixed for the entire family, and acts as a quantization width. Applying \( h_{a,b} \) to a vector or object \( v \) corresponds to the composition of a projection to a random direction (with random offset) and a quantization given by a constant scaling and the floor operation.

B. LSH Indexing

Each individual hash function is locality-sensitive, but not extremely so — there is no particular guarantee making \( p_1 \) close to 1 or \( p_2 \) close to 0, just \( p_1 > p_2 \). In order to make locality-sensitiveness actually useful, LSH employs a function family \( G \), created by concatenating \( M \) hash functions from \( H \), i.e., \( G = g : S \rightarrow U^M \), such that each \( g \in G \) has the following form: \( g(v) = (h_1(v), \ldots, h_M(v)) \), where \( h_i \in H \) for \( 1 \leq i \leq M \).

As we concatenate multiple \( h_i \in H \) functions into a single \( g \), the probability of a false positive (distant vectors hashed together) decreases exponentially. Unfortunately, so increases the probability of a false negative (close vectors hashed apart). In order to solve the latter problem, multiple functions \( g_j \in G \ (1 \leq j \leq L) \) are employed to build \( L \) independent hash tables, in the hope that the good answers will be found in at least one of them. Indyk et al. [23] prove formally that \( M \) and \( L \) can be chosen such that for any query, there is a high probability of finding the right answer, without having to examine too many vectors (false positives). The informal argument that we offer here is that false positives have probability \( p_2^M \), which clearly falls very fast w.r.t. \( M \). As \( L \) grows, both false positives and true positives tend to grow, but the former at a rate related to
Figure 1. The LSH execution scheme may be decomposed into the index building and search phases. In the index building phase, each object in the reference dataset is mapped to a single bucket in each of the \( L \) hash tables using hash function \( g_j(v) \) (first two steps). During the search phase each query object \((q)\) is also mapped to data buckets using the same LSH functions, and those objects stored in buckets to which \( q \) was hashed are selected as candidates, and then ranked according to their actual distance to \( q \) in order to find the \( k \) nearest objects.

\( p_2 \) and the latter at rate related to \( p_1 \) (which is \( > p_2 \)), so it is intuitive that the true positives will grow much faster. Therefore we can find a suitable combination of \( L \) and \( M \), with high true positives and fairly low false positives.

As we have explained in the beginning of the section, LSH may be conceptually decomposed into the phases of index building, and of searching. It is clear now that several hash tables must be employed both during index and search, one for each hashing functions \( g_j \in G \). In the standard implementations, a limit is imposed on the maximum number of candidates to be retrieved (usually \( 2L \) or \( 3L \)) in order to limit the worst case of distances to be computed per query. Also, there is no replication of the dataset: the multiple hash tables only keep a reference to another structure where objects are effectively stored (e.g. a position in an array, or a pointer), so after visiting the buckets, the method has to retrieve the actual data. This is usually fairly cheap for shared-memory environments with uniform access cost. But when access cost is not uniform (disk storage, distributed memory), the implementation of LSH becomes extremely challenging and has been an open problem.

C. Improvements on the basic LSH Indexing

The popularity of LSH motivated much research focused on improving its performance, and reducing its memory footprint. Memory usage is one of the main limitations of the standard LSH, since it has to employ several hash tables in order to reduce the probability of false negatives, a strategy that favors very large values of \( L \) (from a few dozens to a few hundreds). Even though the hash tables store just references, for such large values of \( L \) memory usage quickly becomes a concern.

Entropy-based nearest neighbor search \[25\] is one of the first efforts to address this deficiency. In this approach fewer hash tables are used, but multiple buckets are accessed in each hash table. The buckets visited in each table are chosen by hashing objects randomly selected in the neighborhood of the query object. Because those objects are close to the query object, they are also expected to hash to buckets that have objects similar to the query in the original \( d \)-dimensional space.

Multi-probe LSH \[7\] further extended the entropy based approach with the introduction of a careful methodology for selecting multiple buckets to be accessed in each hash table. Instead of using random objects in the query neighborhood, it estimates the likelihood of a bucket containing good answers from its distance to the query, thus directly deriving the buckets to be visited. This approach typically results, for the same recall, in less bucket accesses per hash table as compared to entropy-base LSH. An extension of this work interprets the likelihoods as full-fledged probabilities, by learning the priors from a sample of the datasets, in a scheme named A Posteriori LSH \[4\]. A Posteriori potentially reduces the number of buckets to visit, but the computation of the list of buckets to visit becomes significantly more expensive.

Several works also studied different locality-sensitive hash functions \[26\]; support for a diversified set of similarity functions \[27\] and improved approach for calculating distance \[28\]; the use of query-adaptive LSH with bucket-filtering based on the query position relative to the quantitized frontier \[2\]; and the automatic tuning of the LSH parameters \[29\], \[30\] such as the number of hash tables to be used.

IV. DISTRIBUTED MEMORY LSH INDEXING

The parallelization strategy we employ is based on the dataflow programming paradigm \[31\], \[32\], \[33\]. Dataflow applications are typically represented as a set of computing stages, which are connected to each other using directed streams. The rest of this section is organized as follows: Section \[IV-A\] presents an overview of our parallelization strategy focusing on the basic LSH method; Section \[IV-B\] discusses the implementation of the intra-stage parallelization; Section \[IV-C\] details different mapping strategies we have evaluated to partition the application state in a distributed environment; and Section \[IV-D\] presents extensions
in our parallel algorithm to support the execution of the multi-probe based LSH scheme.

A. Parallelization Strategy

Our parallelization decomposes LSH into five computing stages organized in two conceptual pipelines, which execute the index building and the search phases of the application (Figure 2). All stages may be replicated in the computing environment to create as many copies as necessary. Additionally, the streams connecting the application stages implement a special type of communication policy referred here as labeled-stream. Messages sent through a labeled-stream have an associated label or tag, which provides an affordable scheme to map message tags to specific copies of the receiver stage in a stream. This tag-to-receiver mapping is computed using a hash function called by the labeled-stream for each message sent. We rely on this communication policy to partition the input dataset and to perform parallel reduction of partial results computed during a query execution. The data communication streams and processes management are built on top of Message Passing Interface (MPI).

The index building phase of the application, which includes the Input Reader (IR), Bucket Index (BI), and Data Points (DP) stages, is responsible for reading input data objects and building the distributed LSH indices that are managed by the BI and DP stages. In this phase, the input data objects are read in parallel using multiple IR stage copies and are sent (1) to be stored into the DP stage (message i) and (2) to be indexed by BI stage (message ii). First, each object read is mapped to a specific DP copy, meaning that there is no replication of input data objects. The mapping of objects to DPs is carried out using the data distribution function obj_map (labeled-stream mapping function), which calculates the specific copy of the DP stage that should store an object as it is sent through the stream connecting IR and DP. This mapping may be calculated based on some characteristic of the object, e.g., its location on the space or simply on the object identifier. Further, the pair <object identifier, DP copy in which it is stored> is sent to each BI copy that holds buckets to which the object was hashed. The distribution of buckets among BI stage copies is carried out using another mapping function: bucket_map, which is calculated based on the bucket value/key. Again, there is no replication of buckets among BIs and each bucket value is stored into a single BI copy.

For sake of simplicity, we assume in this section that both labeled-stream mapping functions (obj_map and bucket_map) are a mod operation that is calculated using either the obj_id or the bucket value (tags) and the number of copies of the receiver stage, e.g., obj_id mod T for the obj_map and DP stage. However, we have evaluated different classes of mapping functions as detailed in Section IV-C.

The labels and the body of messages in the communication from IR to DP and IR to BI are presented in Figure 2. Additionally, it is important to highlight that our labeled-stream implementation employs buffering and aggregation of messages to maximize network performance. Therefore, when messages are dispatched using the stream interface they may be first copied to a buffer for aggregation with other messages before they are sent over the network. This strategy intends to improve performance in the communication among stages such as IR and DP, for instance, in which sending a single small message (object reference) would result in under-utilization of the network and high overheads.

After the index building phase has finished, the buckets created by the L hash tables are distributed through the BI stage copies. Each of the buckets, as discussed, stores only the identifier of the objects and the copy of DP stage in which they are located.

The search phase of the parallel LSH uses four stages, two of them shared with the index building phase: Query Receiver (QR), Bucket Index (BI), Data Points (DP), and Aggregator (AG). The QR stage reads the query objects and calculates the bucket values in which the query is hashed for the L hash tables used. Each bucket value computed for a query is mapped to a BI copy using the bucket_map function. The query is then sent to those BI stage copies that store at least one bucket of interest (message iii). Each BI copy to receive a query message visits the buckets of interest, retrieves the identifier of the objects stored on those buckets, aggregates all object to be sent to the same DP copy (list(obj_id)), and sends a single message to each DP stage that stores at least one of the retrieved objects (message iv). For each message received by a DP copy, it calculates the distance from the query to the objects of interest, selects the k-nearest neighbors objects to the query, and sends those local NN objects to the AG stage. Finally, the AG stage receives the message containing the DPs local NN objects from all DPs involved in that query computation and performs a reduction operation to compute the global NN objects. As presented in Figure 2 (message v), DP copies use the query_id as a label to the message, what guarantees that the same AG copy will process all messages related to a specific query. As a consequence, multiple AG copies may be created to execute different queries in parallel. Although we have presented the index building and the search as sequential phases for sake of simplicity, their execution may overlap.

The parallelization approach we have proposed exploits task, pipeline, replicated and intra-stage parallelism. Task parallelism results of concurrent execution of IR and QR that allows for indexing and searching phases to overlap, e.g. during an update of the index. Pipeline parallelism occurs as the search stages, for instance, execute different queries in parallel in a pipeline fashion. Replicated parallelism is available in all stages of the application, which may have an
Figure 2. LSH decomposition into the dataflow programming paradigm. The index building phase partitions the input dataset among the DP copies without data replication (message i) and the BI stage stores buckets of objects identifiers (message ii). During the search phase the buckets in which the query is hashed are calculated in the QR that communicate with the BI stage to visit those buckets of interest. Further, BI copies send messages to the DPs copies that store at least one point of interest found on the buckets visited. DPs then calculate the local NN using those points it stores. Finally, DP copies will send the local NN results for reduction with the AG stage.

arbitrary number of copies. Finally, intra-stage parallelism results of the application’s ability to use multiple cores within a stage copy as detailed in Section [IV-B]

B. Intra-Stage Parallelization

The intra-stage parallelization refers to a stage ability to execute tasks in parallel using multiple computing cores available in a node. This level of parallelism is important to fully take advantage of current machines, which are typically built as multi-socket, multi-core systems. One of the main advantages in employing intra-stage parallelization, as compared to creating one stage copy per computing core as in classic MPI-based parallelizations, refers to the possibility of sharing the same memory space among computing cores used in a stage copy. In stateful applications such as LSH, a smaller number of state partitions may be created and, as a consequence, a reduced number of messages needs to be exchanged during the computation of a query.

The intra-stage parallelism in our application is implemented using POSIX Threads, and is employed to compute messages arriving at the Buckets Index and the Data Points stages in parallel. These stages have been selected as target for intra-stage parallelization because (i) they are application’s most compute intensive stages and (ii) they store the application index and input dataset (state) and, therefore, this strategy leads to a reduced network traffic and better application scalability. Messages arriving at both stages are independently processed in an embarrassing parallel fashion using all the computing cores available in a node. As discussed, this allows for a single copy of these stages to be created in each machine in which they are executed.

C. Data Partition Strategies

This section considers the partition of the data with our parallel LSH. As presented in the previous section, the buckets_map and obj_map functions are responsible for mapping, respectively, buckets and objects (data points) from the input dataset into one of the BI and DP stage copies. The adequate partition of the dataset is of major importance for the performance, because it directly impacts the number of BI and DP copies that need to be consulted (and messages sent) to process a given query.

Therefore, the partition of the application state should be performed in way to minimize the number of messages exchanged. This resembles the original problem addressed by indexing algorithms, which are in essence trying to partition a high-dimensional space in a way that can be used to efficiently search on that space. To address this challenge, we have studied the impact different mapping functions to the application performance. The functions evaluated include those with locality preserving properties, which would preferably map data points close in the space to the same machine (partition).

The mapping functions analyzed are: (1) a \textit{mod} operation that is calculated based on buckets and data points identifiers and does not preserve data locality (presented in Section [IV-A]); (2) a \textit{space-filling} curve that is a locality preserving fractal curve introduce by Peano and Hilbert \cite{5}. Data points in a d-dimensional space are mapped to a position in the curve, and that position is used as an indicative of how close data points are in the space. We have specifically used the Z-order curve, which is calculate with a bit shuffle and has same properties such as other curves more complex to compute (e.g., Hilbert curve); (3) a \textit{LSH} function that, as discussed, tend to map objects close in the space to the same hash value. This mapping has used an instance of the \textit{g(v)} function (Section [III-B]) different from those used to build the index.
D. Support to Multi-Probe LSH

As previously discussed in Section III-C, LSH may need to use several hash tables to attain the desired search quality, which could lead to high memory usage. Therefore, in our parallel version, we have also developed support for executing the Multi-probe LSH [7] to perform multiple probes \( T \) in each hash table create, such that the desired quality may be reached using a smaller number of hash tables.

In this approach, probes generated for the original query vector have an unique identifier (bucket) in each hash table, and the execution of each of them is treated similarly to an independent query in the search phase pipeline, until the AG stage. During the AG phase, however, those probes generated from the same original query need to be aggregated to create a global unique query answer. In our implementation, we developed an extra message aggregation level in order to pack messages from different probes related to the same query that are routed to the same stage copies. As presented in the experimental evaluation, this approach is very effective and directly impacts in a positive way to the application execution time.

V. EXPERIMENTAL RESULTS

A. Experimental Setup

The experimental evaluation was performed using a distributed-memory machine with 60 nodes. Each computation node is equipped with a dual-socket Intel E5 2.60 GHz Sandy Bridge processor with a total of 16 CPU cores, 32 GB of DDR3 RAM, and runs Linux OS kernel version 2.6.32. The nodes are interconnected through a FDR Infiniband switch.

Table I

| Name     | Reference set size | Query set \((Q)\) size |
|----------|--------------------|------------------------|
| Yahoo    | 130 million        | 233,852                |
| BIGANN   | 1 billion          | 10,000                 |

For the evaluation, we have employed the single most cited feature vectors employed for images, SIFT [34], which have 128 dimensions. Two datasets were used (see Table I). The Yahoo [6] dataset contains about 130 millions SIFT vectors that were extracted from 225 foreground images from our personal collections, and 233,852 background Web images, employed to confound the method. It contains 187,839 query feature vectors created from strong geometric and photometric distortions of the foreground images. The BIGANN [35] is to the best of our knowledge the largest dataset for multimedia retrieval publicly available. It contains 1 billion 128-dimensional SIFT feature vectors computed from 1 million Web images and a query feature vector set with 10,000 vectors. Both datasets have the ground-truth calculated for the query, which is used to evaluate the search quality.

The search quality was the recall [7], which measures the fraction of the true \( k \) nearest neighbors that where effectively retrieved by the method.

B. Assessing the Distributed LSH Scalability

This set of experiments focuses on evaluating the parallel multi-probe LSH scalability. Our analysis employs a scale-up (weak scaling) experiment in which the reference dataset and the number of computing cores used increase proportionally. A scale-up evaluation was selected because we expect to obtain an abundant volume of data for indexing, which would only fit in a distributed system. The Yahoo dataset is used along with a round-robin data partition strategy. Further, the LSH parameters employed are \( L = 6 \) and \( M = 32 \). A detailed evaluation of the parameters impact to the execution times and search quality is presented in the following sections. Additionally, in these experiments a single CPU core is allocated for the AG stage, while the number of computing cores used by the BI and DP stages increase. The ratio of computing cores used by BI:DP stages is 1:4, meaning that for each CPU core allocated to the BI stage 4 CPU cores are assigned to the DP stage. In all experiments in this paper we have requested the algorithm to retrieve the 10-nearest neighbors \((k = 10)\).

The efficiency of the parallel multi-probe LSH as the number of CPU cores and nodes used increase is presented in Figure 3. As shown, the application achieves a very good parallel efficiency, e.g. about 0.9 is attained when 801 computing cores are used (10 nodes for BI and 40 nodes for DP). The high efficiency attained is a result of (i) the application asynchronous design that decouples communication from computation tasks and of (ii) the intra-stage parallelization that allows for a single multi-threaded copy of the DP stage to be instantiated per computing node. As a consequence, a smaller number of partitions of the reference dataset are created, which reduces the number of messages exchanged by the parallel version (using 51 nodes).
in more than $6 \times$ as compared to an application version that instantiates a single process per CPU computing core.

C. Evaluating the Multi-Probe LSH Performance

This section evaluates the distributed multi-probe LSH with respect to the trade-offs between the search quality and execution time as the number of probes ($T$) per table is varied. The BIGANN dataset (1 billion 128-dimensional SIFT vectors and a query set with 10,000 descriptors) is employed, and the LSH parameters chosen after tuning are $L = 6$ and $M = 32$. All experiments are executed using 801 CPU cores/51 nodes.

The compromise between execution time and search quality (recall) according to $T$ is presented in Figure 4. As expected, the recall is improved with the increasing of $T$, but the execution time grows sublinearly with respect to the number probes ($T$) performed. For instance, the variation in $T$ from 60 to 120 results into an execution time increase of only 1.35×, although it was expected that the ratio of the changes in $T$ and execution time would be roughly the same. This is a very good property of our parallel LSH that benefits the use of larger values of $T$ to improve search quality with reduced impact to execution times.

The lower increasing ratio in execution time as consequence of variations in $T$ is a result of: (1) the aggregation of all messages related to bucket visits ($T$ per table) that are routed to the same stage copy; and (2) elimination of duplicated distance calculations that occur when the same data point is retrieve multiple times from different hash tables. The probability of such duplications is higher as $T$ increases. As presented in Table III, the volume of data (GB) and the number of messages exchanged by the application increase, respectively 1.22× and 1.29× as $T$ is varied from 60 to 120.

D. The Impact of LSH Parameters to Performance

This section evaluates the impact of the LSH parameters ($M$ and $L$) to the search quality and execution times using the BIGANN dataset. The value of $M$ (hash functions used per hash table) affects the selectivity of the index. High values of $M$ will lead to reduced probability of mapping far away objects to the same bucket, but too high values may also result in the mapping of close object to different buckets (with smaller probability). The $L$ parameter specifies the number of hash tables used and, as a consequence, visited during the search. A tuning phase is typically employed to determine the optimal values of $M$ and $L$ for a given dataset, since the interactions among these parameters are complex.

In order reduce the combination of parameters evaluated in large-scale experiments in this section, we have first tuned $M$ and $L$ using the sequential version of the multi-probe LSH and a smaller partition of the dataset. Further, we varied $M$ in the neighborhood of the optimal value for the sequential algorithm ($M = 30$) and increased the value of $L$ until we reach the amount of memory available for the BI stage in our configuration.

Table III

| $T$ | Volume of Data(GB) | # of Messages. ($\times 10^{6}$) |
|-----|---------------------|---------------------------------|
| 1   | 2.28                | 1.83                            |
| 30  | 35.73               | 49.43                           |
| 60  | 59.46               | 94.23                           |
| 90  | 79.31               | 136.55                          |
| 120 | 96.82               | 177.08                          |

The impact of varying $M$, for fixed values of $T = 30$ and $L = 6$, is presented in Table III. As expected, the recall slowly decreases with the increasing of $M$ due to the higher selectivity of the hash table. The search time, however, quickly decreases (about an order of magnitude) for values of $M$ higher than 28. This shows that a high selectivity is important for the performance of the algorithm, and that the best value of $M$ for the distributed version is also in the neighborhood of 30.
Finally, Figure 5 shows the performance of the distributed multi-probe LSH as the number of hash tables \((L)\) employed is varied. In these experiments, we have increased the value of \(T\) for each value of \(L\) until the same level of recall is achieved (about 0.74). As shown, the largest number of hash tables lead to better execution times for similar recall values. However, the increasing in the number of hash tables also result into higher memory demands, which limit the number of hash tables that may be used by the application.

E. Effectiveness Of Data Partition Strategies

This section presents an evaluation of the data partitioning using the three mapping functions mentioned in Section IV-C: \(mod\) operation, \(Z\)-order curve, and \(LSH\) function. The BIGANN dataset is used for all experiments, and the LSH parameters chosen are \(L = 6\), \(M = 32\), and \(T = 60\). All experiments used the full environment with 801 CPU cores/51 nodes (10 nodes for BI and 40 nodes for DP).

The execution time and the number of messages exchanged for each mapping function are presented in Figure 6. As may be noticed, the execution time for \(mod\) (246 seconds) and \(Z\)-order (242 seconds) are similar. The use of the \(LSH\) mapping, however, improved the performance on top of the other strategies in at least 1.68×. The differences in execution time are derived from the better \(LSH\) mapping, which also results into lower number of messages exchanged by the application.

We have also evaluate the level of load imbalance regarding the number of objects mapped to each DP copy for each mapping strategy. The load imbalance is defined here as difference from the actual number of data objects assigned to DP copies to the average. For the \(mod\) mapping, as expected, there is no load imbalance, whereas it was 0.01% and 1.80%, respectively, for the \(Z\)-order and \(LSH\). This shows that LSH performs an efficient data partition without incurring in significant load imbalance.

VI. Conclusions and Future Work

The similarity search is one of the most costly phases of query processing in content-based multimedia retrieval applications and, as a consequence, is critical for the success of these services. This paper presents an efficient and scalable LSH based similarity search index for large-scale and high-dimensional multimedia datasets. Our approach addresses the challenges of the LSH indexing parallelization by avoiding data replication, using hierarchical parallelization to take advantage of all CPU cores in a node, studying multiple data partition strategies, overlapping communication and computation, and using a multi-probing strategy to reduce the memory footprint. We evaluated our implementation using a dataset with 1 billion 128-dimensional SIFT feature vectors extracted from images collected in the Web, which is to the best of our knowledge the largest publicly available dataset.

The parallel LSH has attained about 90% of efficiency in a parallel execution using up to 801 CPU cores. In addition, the use of multi-probe with our optimization to group messages resulted into very good trade-offs between quality and search time, since the application execution time grows sublinearly with the increasing of the number of probes \((T)\) performed. We have also shown that there is a strong impact of the number of hash tables \((L)\) and the number of hash functions per hash table \((M)\) to system’s performance. Finally, we presented an evaluation of three data partition strategies, \(mod\) operation, \(Z\)-order curve, and \(LSH\) function, in which the latter attained a performance improvement of at least 1.68× on top of the others.

It is perhaps worth to emphasize that LSH is one of the most important high-dimensional indexes proposed in the literature, but until now, its performance has been confined to shared-memory uniform-access systems, since previous attempts to parallelize it have stumbled upon the challenge of adapting its lack of referential locality to scalable, distributed memory architectures. By addressing those challenges, our technique brings one of the most successful sequential high-dimensional indexes to the operational scenario of large-scale online content-based multimedia services. As future work, we plan to use accelerators, such as GPUs and Intel Xeon Phi, to perform coordinated LSH execution using CPUs and accelerators \([36, 37, 38, 39]\). We also want to test our implementation in other areas, such as biology, in order to find similarities in genomic databases.

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