SOM-BASED K-NEAREST NEIGHBORS SEARCH IN LARGE IMAGE DATABASES

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Abstract

We address the problem of K -Nearest Neighbors (KNN) search in large image databases. Our approach is to cluster the database of n points (i.e. images) using a self-organizing map algorithm. Then, we map each cluster into a point in one-dimensional distance space. From these mapped points, we construct a simple, compact and yet fast index structure, called *array-index*. Unlike most indexes of KNN algorithms that require storage space exponential in dimensions, the *array-index* requires a storage space that is linear in the number of generated clusters. Due to the simplicity and compactness of the *array-index*, the experiments show that our method outperforms other well know methods.

1. INTRODUCTION

A wide range of database applications requires the ability to answer queries based on similarity. In a database of n points, given a query point $\mathbf{q}$ (a d -dimensional vector), we want to return the K points in the database that are

most similar to $\mathbf{q}$. Those K points are called the K -Nearest Neighbors (KNN) to $\mathbf{q}$. Finding KNN points is one of the most expensive operations in high-dimensional databases, such as image databases [1], time series databases [2], data mining [3], etc. However, KNN search is an essential requirement to most of these applications.

In this paper, we propose a new KNN search approach based on clustering the image data and then using the representative vectors of these clusters to build a simple, compact and yet efficient index structure. First, using a wavelet transform method, we extract the color feature of each image in the database; thus, mapping an image into a point in a high-dimensional feature space. Then, these high-dimensional points are clustered based on their similarity using a self-organizing map (SOM) algorithm. Each formed cluster C_i is represented by a d -dimensional vector $\mathbf{m}_i$, called *codebook vector* (CBV), where d is the dimensionality of the input points.

From among the CBVs, a reference point $\mathbf{R}$ is selected, then the distance $D(\mathbf{m}_i, \mathbf{R})$ between each $\mathbf{m}_i$ and $\mathbf{R}$ is computed. Using $\mathbf{R}$ and the computed distances, we map the CBVs of the clusters into a 1-dimensional distance space in which the mapped clusters are ordered based on their similarity to $\mathbf{R}$. Since the number of clusters N_C is very small as compared to the number of images N_I in the database, we can use a simple sorted array structure, called *array-index*, to index these clusters. Using a simple sorted array structure allows us to find the most similar C_i , called a *winner node* (WN), to a given $\mathbf{q}$ using the fast binary search algorithm whose complexity is $O(\log N_C)$. As a result, fast KNN search in large image databases is achieved.

The rest of this paper, is organized as follows: Section 2 describes some of the related work. Section 3 discusses how to generate and cluster the data, then build the *array-index*. In Section 4, we present the KNN search algorithm. The experiments are discussed in Section 5. Finally, we conclude the paper in Section 6.

2. RELATED WORK

The problem of finding the exact, or approximate, KNN points in a database to a given query point has been addressed by a large number of works. Most of these works have provided good solutions for the low-dimensionality case, but for the high-dimensionality case there have been very little progress. The following are some examples of the related work.

Multi-dimensional index structures, such as the R*-tree [4] is known to perform well as compared to many other multi-dimensional index structures. However, performance of the R*-tree degrades as dimensionality increases [9]. Newly proposed trees such as the X-tree [5] improves performance over that of the R*-tree by extending the overflowed nodes into super nodes. Another new

index, called the A-tree [10], improves performance in high-dimensional space by storing virtual bounding rectangles instead of the actual MBRs.

Other methods apply “dimensionality reduction” techniques on the data points before inserting them into the trees. The QBIC system [11] of IBM uses a bounding method to map the high-dimensional color histograms of images into points in a 3-dimensional space and then organizes those points by an R*-tree. Chakrabarti et. al. [12] utilizes the Principle Component Analysis method to reduce the dimensions of the locally correlated clusters, then each locally correlated cluster is indexed by a hybrid tree. The resulting hybrid trees are then joined by a global index. However, this system requires expensive preprocessing of the data to find the correlated clusters and reduce the dimensions.

Some other algorithms are proposed to return exact KNN answer points, others return approximate KNN answer points. Roussopoulos et. al. [14] proposed an algorithm that starts at the root of the tree and performs a depth-first traversal to find the exact KNN points. Berchtold et. al [7] proposed a different approach that precomputes the result of any nearest neighbor search that corresponds to a computation of a voronoi cell of each data point. Then, they use an X-tree to store the voronoi cells. Other approaches, such as the works proposed by Kleinberg [8] and by Brin [15], have settled for approximate KNN in return of better performance. Although finding approximate KNN answer points to a given query point is of use in some applications, finding exact KNN answer points is our goal in this paper.

3. BUILDING THE INDEX

One of the goals of this paper is to build a simple, compact and yet fast index structure for our image database. Hence, the core of our new approach is to reduce the size of the index structure in order to speed up the KNN search. The size-reduction of the index structure is achieved by, first, clustering the data points (i.e. images) and, then, indexing the clusters rather than the data points themselves, as explained below.

3.1. Wavelet Transformation

We are using a Haar wavelet transform to decompose images into several frequency bands and then compute a feature vector from these bands. As a result of using the Haar wavelet transform, the generated feature vectors are compact since we can use only a few coefficients to sufficiently represent the image color content. Moreover, the Haar wavelet basis is the simplest wavelet basis, in terms of implementation, and the fastest to compute [16].

3.2. SOM-Based Clustering

According to [17], the SOM is unsupervised neural network that maps high-dimensional input data $\mathcal{R}^n$ onto a usually two-dimensional output space while preserving the topological relations (similarities) between the data items. The SOM consists of nodes (neurons) arranged in a two-dimensional rectangular or hexagonal grid. A *codebook vector* (CBV) $\mathbf{m}_i \in \mathcal{R}^n$ is associated with every node i . An input vector $\mathbf{x} \in \mathcal{R}^n$ is compared with the $\mathbf{m}_i$, and the best-matching-node (BMN), which has the smallest Euclidean distance $D(\mathbf{x}, \mathbf{m}_i)$, see Equation 1, is selected. The input is thus mapped onto the location of the selected BMN.

$$D(\mathbf{x}, \mathbf{m}_i) = \left(\sum^{N_d} (\mathbf{x} - \mathbf{m}_i)^2 \right)^{1/2} \quad (1)$$

Where, N_d is the dimensionality of the input vectors. The CBV $\mathbf{m}_c$ of the BMN is adopted to match the input vector. That is done by moving $\mathbf{m}_c$ towards $\mathbf{x}$ by a certain fraction of the distance $D(\mathbf{x}, \mathbf{m}_c)$. Moreover, the CBVs of nodes in the neighborhood of the BMN are moved towards $\mathbf{x}$, but to a lesser extent than the CBV of the BMN. This learning process finally leads to a topologically-ordered mapping of the input vectors. That means the similarity between data points and between clusters are represented in the map. The CBV of a node (cluster) is quite representative of all points within the node. In this paper, we will use the terms node and cluster alternatively.

3.3. Cluster Mapping

After generating the clusters by a SOM, we propose to index the clusters' CBVs instead of the data points themselves. As a result, our index structure is not only simple, but also compact. The most convenient data structure that can efficiently accommodate such a small number of clusters is a sorted array, called *array-index*. The idea is to map the clusters' CBVs from the 2-dimensional SOM grid into a 1-dimensional distance space, as discussed below.

3.3.1 Reference Point Selection. For the image database that we used in our experiments, we found that selecting a reference node $\mathbf{R}$ at the center of all nodes in the SOM grid (called, center $\mathbf{R}$) leads to a slightly faster search time than selecting a reference node at the edge of all nodes in the SOM grid (called, edge $\mathbf{R}$). That is because a center $\mathbf{R}$ leads to a more sparse mapping (less overlapping between clusters); thus, for a given query $\mathbf{q}$ the search space decreases.

3.3.2 Distance Computation. After selecting $\mathbf{R}$, we compute the Euclidean distance $D(\mathbf{R}, \mathbf{m}_i)$ between $\mathbf{m}_i$ of each CBV and $\mathbf{R}$. By computing these distances, we actually map the CBVs into a one-dimensional distance space as illustrated in Figure 1. Such mapping is necessary for the following reasons:

(1.) Arranging the CBVs in a 1-dimensional distance space enables us to use the fast binary search algorithms to find a certain cluster in $O(\log N_C)$ time, where N_C is the number of clusters.

(2.) During clustering, the SOM cannot position all similar clusters next to each other in the grid due to its geometry; therefore, mapping those clusters into a 1-dimensional distance space corrects clusters' layout by bringing together similar clusters next to each other. However, clusters that are equidistant from $\mathbf{R}$, although not necessarily similar, are placed next to each other in the 1-dimensional space. These equidistant clusters are pruned during the KNN search as we will explain in Section 4.

Figure 1. Mapping SOM clusters into a 1-dimensional distance space.

It is worth mentioning that a SOM can map clusters into a 1-dimensional space (instead of into a 2-dimensional space), but the one dimensional space will have the same problem of the 2-dimensional space where similar clusters can not be positioned next to each other. Thus, a remapping is necessary.

3.3.3 array-index Construction. The computed distances $D(\mathbf{R}, \mathbf{m}_i)$ are inserted into the *array-index*. Along with each distance, a pointer to the best-matching-list (BML) of the corresponding cluster is set. The BML of cluster C_i is a list of images associated the C_i . Also, for every C_i , we compute its radius r_i that reflect the size of C_i (see Section 4.1 for a formal definition of r_i). The constructed *array-index* is very small in size since it only contains three fields (distance, pointer, radius) for every generated cluster. Therefore, the *array-index* can be updated, resized or rebuilt with a very small overhead that is compromised by the fast search time it provides.

Most KNN algorithms either require a storage space exponential in dimension, or require a query time not much better than a linear scan [8]. In our method, the size of the *array-index* does not depend on the dimensions of data, but it requires a storage space that is linear in the number of clusters, as opposed to dimensions.

4. K-NEAREST NEIGHBORS SEARCH

Given a query image $\mathbf{q}$, we want to retrieve the exact KNN images. Our KNN search algorithm starts by finding the *winner node* (WN), which is a node with the most similar CBV to $\mathbf{q}$, on the *array-index*. Then, as shown in Figure 2, the algorithm continues the search for similar clusters on both the left and right directions of the WN. During the search, dissimilar clusters are pruned based on some pruning condition (see Equation 4). Based on an ending condition (see Equation 5), the search ends when all KNN images are retrieved and further checking of new clusters does not result in new KNN answer images. Before, discussing the details of our KNN search algorithm, we introduce the pruning and ending conditions.

Figure 2. Searching to the left and right of the winner node (WN).

4.1. Conditions for KNN Search

To achieve efficient computation of the exact KNN answer points (i.e. images), our KNN search algorithm requires conditions on which pruning dissimilar clusters and ending the KNN search are based. Let r_i be the radius of cluster C_i and r_{max} be the largest radius among the radii of all clusters. Formally,

Definition 1 Let P be a set of points in C_i , then, radius r_i is the largest distance between the CBV $\mathbf{m}_i$ of C_i and any point $p \in P$.

$$r_i = \{D(\mathbf{m}_i, p) | p, \hat{p} \in P : p \neq \hat{p} : D(\mathbf{m}_i, p) \geq D(\mathbf{m}_i, \hat{p})\} \quad (2)$$

Definition 2 Let S be a set of radii of all clusters, then r_{max} is the maximum radius in S .

Figure 3. (a) An illustration of a radius of a cluster, (b) the image points on the 1-dimensional distance space.

$$r_{max} = \max\{r_i | r_i \in S\} \quad (3)$$

Figure 3 shows the mapping of image points, which are associated with cluster C_i , onto the 1-dimensional distance space based on their Euclidean distances from m_i . Clearly, image points that are equidistant from m_i are mapped to the same position on the 1-dimensional distance space.

4.1.1 Pruning Condition. Let D_{knn}^c be the current largest distance in the KNN list. Hence, cluster C_i is pruned if the distance between q and the closest point in C_i to q is greater than D_{knn}^c (see Figure 3.a). Formally,

Condition 1 During the KNN search, cluster C_i is pruned if the following condition holds true:

$$|D(q, m_i)| - r_i > D_{knn}^c \quad (4)$$

To assure that our pruning condition does not miss any qualifying clusters, we need to prove that cluster C_i is pruned only if the distance D_{knn}^c is less than, or equal to, the distance between q and any point in C_i . Formally, we need to prove:

Lemma 1 $D_{knn}^c \leq D(q, p)$, where $p \in P$, and P is a set of all image points in the pruned C_i .

Proof: By Definition 1, r_i is the largest distance $D(m_i, p)$, where $p \in P$ and P is a set of all points in the pruned C_i . Refer to Figure 3, if p is on the circumference of C_i , then p is at distance r_i from m_i ; thus, $|D(q, m_i)| - r_i = D(q, p)$. Otherwise, if p is inside the perimeter of C_i , then p is at a distance less than r_i from m_i ; thus, $|D(q, m_i)| - r_i < D(q, p)$. And, since

$|D(\mathbf{q}, \mathbf{m}_i)| - r_i > D_{knn}^c$ (see Equation 4), we conclude that $D_{knn}^c \leq D(\mathbf{q}, \mathbf{p})$. Proof is Complete.

4.1.2 Ending Condition. Most of the previous KNN search algorithms, such as [14], traverses the whole index structure, except for the pruned branches; as a result, a large number of nodes are accessed. Therefore, we need to determine a condition on which the KNN search ends as soon as the exact KNN answer points are retrieved without the need to traverse the whole index structure.

To guarantee that no qualifying image points are missed, the search should not end if there exist a cluster overlapping D_{knn}^c because there might be an image point, in the overlapped portion of the cluster, whose distance from $\mathbf{q}$ is smaller than D_{knn}^c . That is we need to check all clusters whose $\mathbf{m}_j$ are in the vicinity of D_{knn}^c point up to r_{max} (that is $D_{knn}^c + r_{max}$) because r_{max} specifies the position of the farthest possible $\mathbf{m}_j$ of C_j that might be overlapping with D_{knn}^c . Formally, we state the ending condition of the KNN search as follows:

Condition 2 *The KNN search ends when the following condition holds true in both the left and right directions:*

$$D_{knn}^c + r_{max} < |D(\mathbf{q}, \mathbf{m}_i)| \quad (5)$$

Let the largest distance in the final KNN list be D_{knn}^f . To guarantee that the KNN search stops without missing any qualifying image points, we need to prove that D_{knn}^f is less than, or equal to, the distance between $\mathbf{q}$ and any image point in the set of all unchecked clusters. Formally, we need to prove that:

Lemma 2 $D_{knn}^f \leq D(\mathbf{q}, \mathbf{u})$, where, $\mathbf{u}$ is a point such that $\mathbf{u} \in U$ and U is a set of all unchecked clusters.

Proof: By Definition 2, r_{max} is the maximum radius among the radii of all clusters. For any unchecked cluster that is overlapping with D_{knn}^c , we find $r_{max} \geq \max\{|D(\mathbf{q}, \mathbf{m}_i)| - D_{knn}^c\}$, where $\mathbf{m}_i$ is the CBV of an unchecked cluster. That means, by checking all clusters whose $D(\mathbf{q}, \mathbf{m}_i)$ is less than, or equal to, $D_{knn}^c + r_{max}$ we can guarantee that no other cluster $C_j \in U$ has an image point $\mathbf{u}$ with $D(\mathbf{q}, \mathbf{u})$ less than D_{knn}^c . Therefore, D_{knn}^f is less than, or equal to, the distance between $\mathbf{q}$ and any image point $\mathbf{u}$ in the set of unchecked clusters. Proof is complete.

4.2. KNN Search of array-index

Let's first explain some of the routines and notations in the *KNN_Search* algorithm, which is shown below. The *KNN_List* keeps the distances of, and

pointers to, the K most similar images to q . The $update_KNN_list(C_{ptr})$ routine computes the distances between q and each of the image points associated with the cluster pointed at by C_{ptr} and updates the KNN_list according to the computed distances. $Lptr$ and $Rptr$ are pointers used to traverse the $array_index$ toward the left and the right of WN , respectively.

Algorithm: KNN_Search

Input: query image q and the $array_index$

Output: KNN_list of images

1. $WNptr = find_WN(q)$
2. $update_KNN_list(WNptr)$
3. $Lptr = Rptr = WNptr$
4. $KnnFound = FALSE$
5. $LeftSearchEnded = RightSearchEnded = FALSE$
6. $TraverseLeft = TraverseRight = TRUE$
7. While(NOT $KnnFound$)
8. If (NOT $LeftSearchEnded$ AND $TraverseLeft$)
9. compute $|D_L(q, m_{Lptr--})|$
10. If $(D_{knn}^f + r_{max} < D_L - r_{Lptr})$ $LeftSearchEnded = TRUE$ and go to step 12
11. If $(D_L - r_{Lptr} > D_{knn}^c)$ prune C_{Lptr} and go to step 8
12. If (NOT $RightSearchEnded$ AND $TraverseRight$)
13. compute $|D_R(q, m_{Rptr++})|$
14. If $(D_{knn}^f + r_{max} < D_R - r_{Rptr})$ $RightSearchEnded = TRUE$ and go to step 16
15. If $(D_R - r_{Rptr} > D_{knn}^c)$ prune C_{Rptr} and go to step 12
16. $TraverseLeft = TraverseRight = TRUE$
17. If ($LeftSearchEnded$ AND $RightSearchEnded$) $KnnFound = TRUE$
18. Else If (NOT $LeftSearchEnded$ AND NOT $RightSearchEnded$)
19. If $(D_L < D_R)$ $update_KNN_list(C_{Lptr})$; $TraverseLeft = FALSE$
20. Else $update_KNN_list(C_{Rptr})$; $TraverseRight = FALSE$
21. Else If ($LeftSearchEnded$ AND NOT $RightSearchEnded$) $update_KNN_list(C_{Rptr})$
22. Else If (NOT $LeftSearchEnded$ AND $RightSearchEnded$) $update_KNN_list(C_{Lptr})$
23. return KNN_list

The first essential step in the KNN_Search is to find WN , which is a cluster whose CBV is the most similar to q , as in line 1. In line 2, the KNN_list is updated with the image points associated with the WN . Line 3 initializes $Lptr$ and $Rptr$ to the value of the pointer that points to WN . Lines 4-6 defines boolean variables used to control the ending of a search, pruning of dissimilar clusters, and traversal to the left and right of the WN . The search for KNN points is contained in the loop between lines 7-23. Lines 8-11 traverse the $array_index$ towards the left of WN . The distance between q and the m_{Lptr} of the next unvisited cluster to the left of WN is computed, as shown in line 9. Then, in line 10, the ending condition for the left traversal is checked and the left traversal is ended if the condition holds true. Otherwise, if the left traversal is not ended, the currently visited cluster is checked against the pruning condition, if it holds true, the currently visited cluster is pruned and the algorithm advances

to the next unvisited cluster in left direction. The right traversal (lines 12-15) is similar to that of the left traversal.

Lines 16-17 check if both traversal directions (left and right) have been ended. If so, the search ends and the *KNN_Search* algorithm returns the *KNN_list*. In lines 18-20, if the left traversal and right traversal have not been ended, then the *KNN_list* is updated with one of the two currently visited cluster (the one with the smaller distance from *q*), then the traversal in the opposite direction is blocked temporarily, so that the next iteration of the algorithm fetches the next cluster in the direction of the currently visited *closer* cluster (the one with the smaller distance) and keeps the currently visited *farther* cluster for the next comparison. Line 21 handles the case when the left traversal is ended and the search is advancing only in the right direction, thus, the *KNN_Search* algorithm updates the *KNN_list* with the next qualifying cluster on the right direction. Similarly, in lines 22, the search only advances in the left direction. In line 23, the *KNN_list* is returned with the exact KNN answer points.

5. EXPERIMENTS

We performed our experiments on collected images from publicly available image databases; *H² Soft* [18] and Stanford University [19]. The size of the collected image database is 40,000 artificial and natural images that span the following categories: landscapes, animals, buildings, people, plants, CG, etc. The image size is fixed at 128×128 pixels. We performed the experiments on an EPSON DIRECT PC (RAM: 128 Mbytes and CPU: Celeron 700 MHz) with a FreeBSD4.2 OS.

We extracted the color feature of each image using the Haar wavelets (see Section 3.1). The color space used in this paper is the YIQ color space since it exploits certain characteristics of the human eye, where Y carries luminance information and I and Q carry color information and some luminance information. The color feature for each image is represented by a *d*-dimensional vector. To demonstrate the efficiency of our KNN search algorithm, we generated 3 databases with different dimensionalities: 3, 12, and 48 dimensions by applying a 7-level, 5-level, and 3-level decomposition, respectively, of the Haar wavelet transform on the image data.

From each database (3, 12, and 48 dimensions), we generated different test data sets 1K, 5K, 10K, 20k, 30k, 40k vectors, where $k = 1000$. Each of these data sets was clustered by a SOM, as explained in Section 3.2. As shown in Table 1, we specified two map sizes (numbers of SOM nodes) for each data set: ‘fixed map size’ and ‘adaptive map size’.

Fixed and Adaptive Map Sizes: The fixed and adaptive map sizes of each set reflect the maximum number of possible clusters and are used as parameters for the SOM. Hence, for each data set we generated two sets of clusters.

Table 1. Map sizes ('fixed' and 'adaptive') of each data set.

Data set	Map size	
	fixed map size	adaptive map size
1000	20 × 20	30 × 30
5000	30 × 30	70 × 70
10000	30 × 30	100 × 100
20000	30 × 30	130 × 130
30000	30 × 30	170 × 170
40000	30 × 30	200 × 200

The number of nodes of the 'fixed map size' is small as compared to the cardinality of (number of images in) the database; thus, the number of generated clusters is almost equal to the specified number of nodes. On the other hand, for the 'adaptive map size', the number of specified nodes is equal to the number of images in the corresponding data set; thus, clustering the data generated empty nodes (nodes containing no images). As illustrated in Figure 4, the number of generated clusters in the 'adaptive map size' is adaptive to the size of the database (the number of clusters increases as the size of the database increases), where the number of generated clusters is decided by the SOM algorithm based on the features of input database. Also, we notice that the 12-dimensional data sets have lower number of empty nodes than those of the 3-dimensional and 48-dimensional data sets. That is because the data sets in the 12-dimensional space are more sparse, hence occupies more clusters. On the other hand, the data sets in 3-dimensional space suffers from high degree of detail loss leading to large number of false similarities and bigger, but fewer, clusters. Also, in the 48-dimensional space, there is more overlap between image vectors due to the 'dimensionality curse' leading to less number of clusters as compared to the 12-dimensional clusters.

Search Efficiency: To analyze the effect of dimensionality on the KNN search time, we measured the search time of data sets of different sizes and different dimensionalities, as shown in Figure 5. First, we randomly selected 10 images from the database and issued a query to retrieve the KNN (where, $K=1$ and $K=100$) answer images for each of the different sizes and different dimensionalities. The search times shown in Figure 5.a and 5.b are the average of 10 queries. We notice that for both $K=1$ and $K=100$ the 12-dimensional data sets have lower KNN search time than the 3-dimensional and 48-dimensional data sets especially when the size of the data sets increases (≥ 10000). That is because the 12-dimensional data is more sparse, thus occupying more clusters; as a consequence, when a query is issued only a fewer number of clusters is needed to be accessed to retrieve the KNN images as compared to the other dimensionalities.

Figure 4. The number of empty nodes in the three databases: 3-dim DB, 12-dim DB, and 48-dim DB.

Figure 5. Average KNN search time versus database size when (a) $K = 1$, and (b) $K = 100$.

To prove the above reasoning, we measured the percentage of visited non-empty (associated with one or more images) clusters accessed to retrieve the KNN images to a given query (see Figure 6). We notice that, for both cases $K=1$ and $K=100$, the percentage of visited nodes of the 12-dimensional data is lower than those of the 3-dimensional and 48 dimensional data especially for data sets ≥ 10000 images.

To analyze the dynamics of the *array-index* method, first, we clustered a small data set, which is 5000 image, using the ‘fixed map size’ (30×30) as a parameter for the SOM algorithm and measured the KNN search time. Then, as shown in Figure 7, we increased the size of the database to 10000, 20000, 30000, and 40000 images and measured the KNN search time at each database size. The test shown in Figure 7 is for a database with 48 dimensions and $K=1$. We notice, for the ‘fixed map size’, as the database size increases the KNN

Figure 6. The percentage of the accessed database (visited nodes) versus database size when (a) $K = 1$, and (b) $K = 100$.

Figure 7. Comparison between the 'fixed map size' and 'adaptive map size' to show the dynamic extent of the array-index method (dimensions = 48, and $K = 1$).

search time increase slightly up to the database size of 30000, and beyond that size the KNN search time shoots up with great increases. The reason is that beyond the database size of 30000 images the size of clusters become very big (containing large number of images); thus, the number of false alarms for a given query increase greatly in the clusters leading to many distance computations to remove those false alarms and hence increases the KNN search time. Thus, we conclude that beyond the database size of 30000 the system should recluster the database with an increase in the map size (number of clusters). As a comparison, in Figure 7, we show the KNN search time of the same data sets but with different number of clusters (using the 'adaptive map size', see Table 1).

Figure 8. Comparison between the array-index method and a linear scan method in terms of KNN search time versus number of dimensions: (a) for $K = 1$, and (b) for $K = 100$.

Comparative Study: According to [8], most KNN search algorithms, require a search time not much better than a linear scan. We compared the *array-index* method with other well known methods (R*-tree and linear scanning), which serve as a stick-yard to evaluate our method, in terms of KNN search time. Figure 8 shows the comparison between the three methods for $K=1$ and $K=100$ using a database of size 20000 images. Obviously, the *array-index* method outperforms the other two methods, R*-tree and linear scanning, particularly, at high-dimensionalities (≥ 12 dimensions), which are the bottlenecks for most KNN search algorithms. The KNN search time of the linear scanning methods increases linearly with the number of dimensions and the search time of the R*-tree increases exponentially with the number of dimensions. On the other hand, the *array-index* method shows more robustness to the number of dimensions since the KNN search time only increases slightly as the dimensionality increases. Clearly, the *array-index* method reduces the search space greatly due to its simple and compact structure.

6. CONCLUSION

We presented a simple and efficient method, called *array-index*, to retrieve exact K -nearest neighbors for a given query. The *array-index* method is based on clustering the data and then indexing the clusters' representative vectors instead of the data points themselves; thus, reducing the size of the index structure. Although, we clustered the database using a SOM algorithm, the *array-index* method will work well with any clustering technique. The compactness and the ordering of clusters in the *array-index* are the main reasons behind the fast KNN search time as compared to other known methods. The compactness of the *array-index* enabled us to put the whole index structure

in memory leading to an elimination of I/O cost, and the ordering of clusters based on their distances from a reference point helped reducing the percentage of accessed database necessary to determine the exact KNN answer images.

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