Efficient Indexing, Shape Descriptors and Browsing in Image Databases by using D-index Structure

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ABSTRACT:*Thanks to the development of technology of image productions and processing, the need of avoiding the traditional research based on user's annotation is becoming more interesting; the content based image retrieval technology provides several techniques to solve this problem. In this paper we aim to propose and evaluate the combined use of D-index structure and smooth curve decomposition descriptor so as to enable accurate and fast content based image retrieval. Furthermore, this work provides an experimental analysis of D-index parameter choice and an experimental demonstration of the efficiency of D-index method through comparing its results with other known ones.*

Keywords: Content Based Image Retrieval, Index Structure, Descriptors, D-index, Smooth Curve Decomposition

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1. Introduction

For the past few years, the content based image retrieval is become a more interesting research topic, its mission is to searching images similar to image query in large images databases, many search works are proposed, they provide several techniques and methods in this area, and can be classified in two important domains; techniques of description of visual image content [1] and techniques of indexing image databases [2].

Description of *visual images content*; requires to extract the visual characteristic content of images, the most popular characteristics are based on color [3], texture [4] and shape [5].

Indexing image databases; is an important research topic in content based image retrieval; due to the high dimensionality of the descriptor used, the cost of searching in image databases is too expensive, so we have to index the databases into an adequate structure to minimize the cost of browsing and searching. Several methods are proposed in the literature [2], they can be classified into two types; methods based on data partitioning [6] like M-tree, R-tree,… and others based on space partitioning [7] like P+-tree, Pyramide …

In this paper we propose a content based image retrieval system by using smooth curve decomposition [8] and the distance of hausdorff to compare shapes, and also by using D-index [9] [10] to index the databases. The remainder of the paper is organized as follows. In section 2 we talk aboutthe description of visual image content, especially we present an overview of shape representation and we define the descriptor "*smooth curve decomposition*". In Section 3 we present the definition of Metric space and the general principals of D-index structure. Several retrieval examples, an experimental analysis of D-index parameter choice, and a comparative analysis are presented in section 4. Finally, the conclusion and future investigations are discussed in section 5.

2. Descripiton of visuel image content

2.1 Shape representation

Shape is an important visual feature and it is one of the basic features used to describe image content; it's often corrupted with noise, defects, arbitrary distortion and occlusion. In [5] D.Zhang et al classified Shape representation and description techniques into two classes of methods:contour-based methods and region-based methods.

Contour-based methods only exploit shape boundary information, in region-based methods all pixels within a shape region are taken into account to obtain the shape representation. Figure 1 show the hierarchy of this classification.

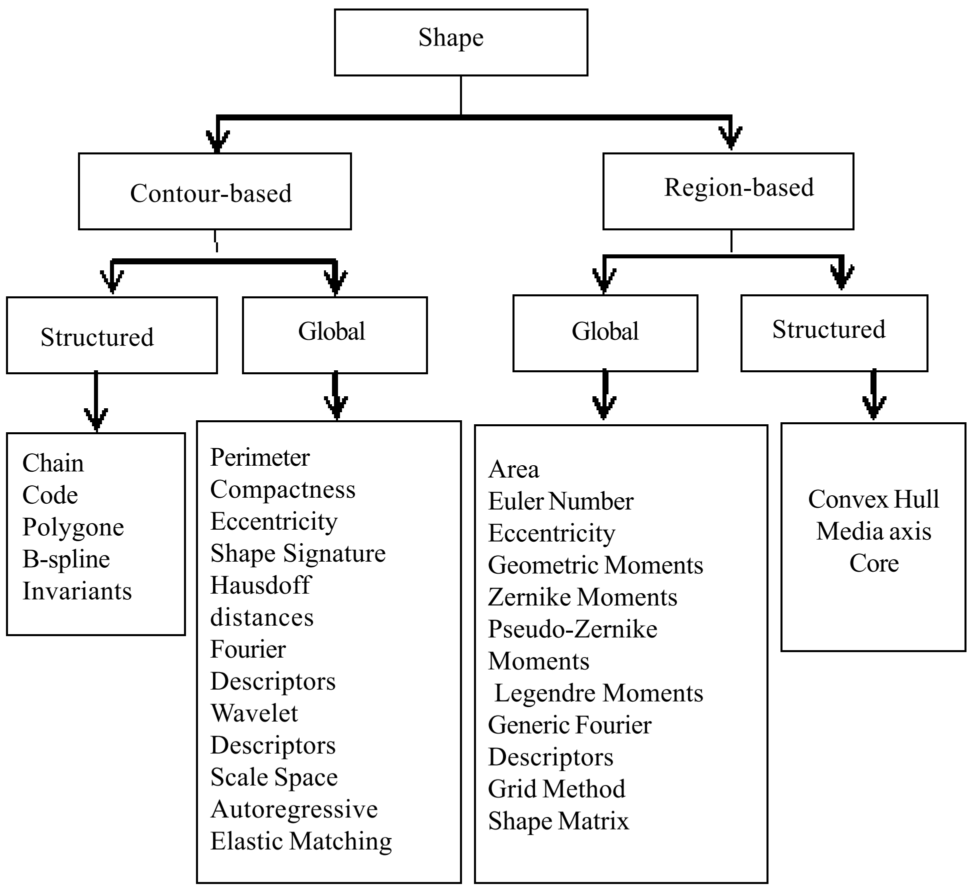

Figure 1. Classifcation of shape representation and description techniques

In this article we propose to use the "*Smooth curve decomposition to describe descriptor*", which is robust with respect to noise, scale of the objects. It is based on curvature extreme are known to be more stable [11] [12] than curvature inflection points (zero crossings).

2.2 Smooth curve decomposition

In [8], the authors proposed smooth curve decomposition as a shape descriptor. The segment between the curvatures zero-crossing points from a Gaussian smoothed boundary are used to obtain primitives, called tokens. The feature for each token is its maximum curvature and its orientation. In Figure 2(b), the first number in the parentheses is its maximum curvature and the second is its orientation.

The similarity between two tokens is measured by the weighted Euclidean distance. The shape similarity is measured according to a non-metric distance.

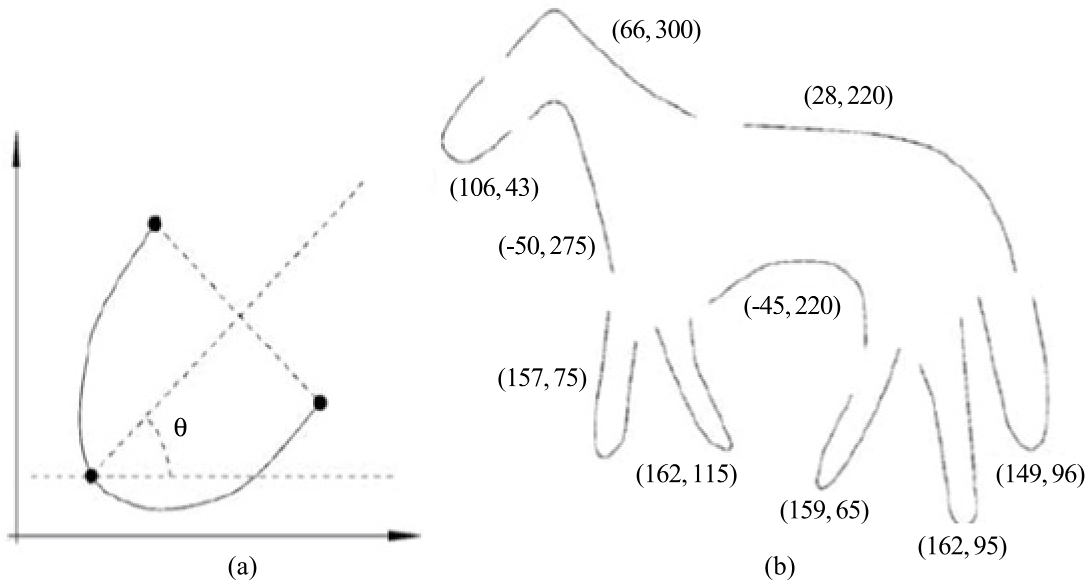

Figure 2. (a) Token representation, and its orientation θi. (b) Shape of a horse is partitioned at minima of the curvature function [8]

Shape retrieval based on token representation has shown to be robust in the presence of partially occulted objects, translation, scaling and rotation [13]. In this paper we propose to use the hausdorff distance to compare two shape instead of measure used in [8]

3. Indexing Metric space

3.1 Metric space

Let $M = (D, d)$ be a metric space for a domain of objects D and d: $D \times D \rightarrow R$, a total distance function that satisfies the following properties:

$$\forall x, y \in D, d(x, y) \geq 0$$
$$\forall x, y \in D, d(x, y) = d(y, x)$$
$$\forall x, y \in D, d(x, y) = 0 \Longleftrightarrow x = y$$
$$\forall x, y, p \in D, d(x, y) \leq d(x, p) + d(p, y)$$

To retrieve elements similar to object O, there are two types of query; *range query* for $q \in D$ and a range r retrieves all the objects within distance r , that is the set $\{x \in X \,|\, d(x, q) < r\}$, *nearest neighbor query* returns the k closest elements to the *query object* q, *or the set* $R \subseteq X$ *such that* $|R| = k$, *for any* $x \in R$ *and any* $y \in X - R : d(q, x) \leq d(q, y)$.

3.2 D-index methods

The main goal of metric access methods is to reduce as much as possible the number of distance evaluations needed to solve a query, The D-index, regarded as one of the fastest MAMs available, was presented in [9] [10], its principle idea is based on portioning data into subsets organized in h levels and each level content $2^{n_i} - 1$ separable buckets plus another bucket called exclusion bucket for capture all objects that can not be stored in previous levels. An example of D-index structure is shown in figure 3.

The construction of D-index based on particular functions called ρ − split functions, has as a goal the partitioning of the

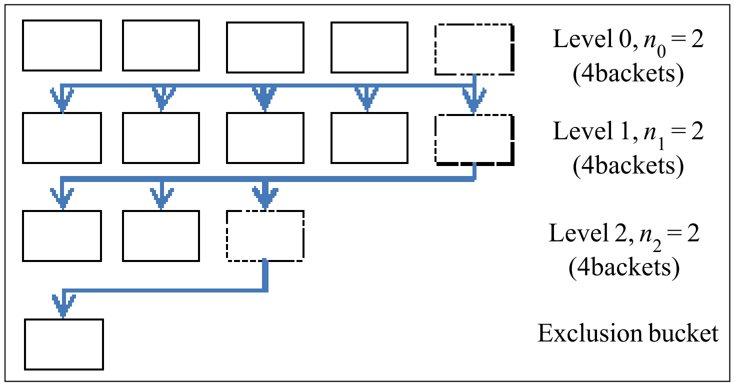

Figure 3. structure of D-index

databases into buckets separable up to 2ρ; several ones are proposed in [14]. For example; The ball partitioning ρ – split function $bps^{\rho}(X, X_v)$ defined in following (scheme 1) uses one object $X_v \in D$ and the medium distance d_m to partition data into three subsets $BPS^{1,\rho}_{[0]}$, $BPS^{1,\rho}_{[1]}$ and $BPS^{1,\rho}_{[2]}$ (see figure 4).

$$bps^{1,\rho}(x, x_v)\begin{cases} 0 & if\,(x, x_v) \le d_m - \rho \\ 1 & if\,(x, x_v) > d_m + \rho \\ & -\,otherwise \end{cases}$$

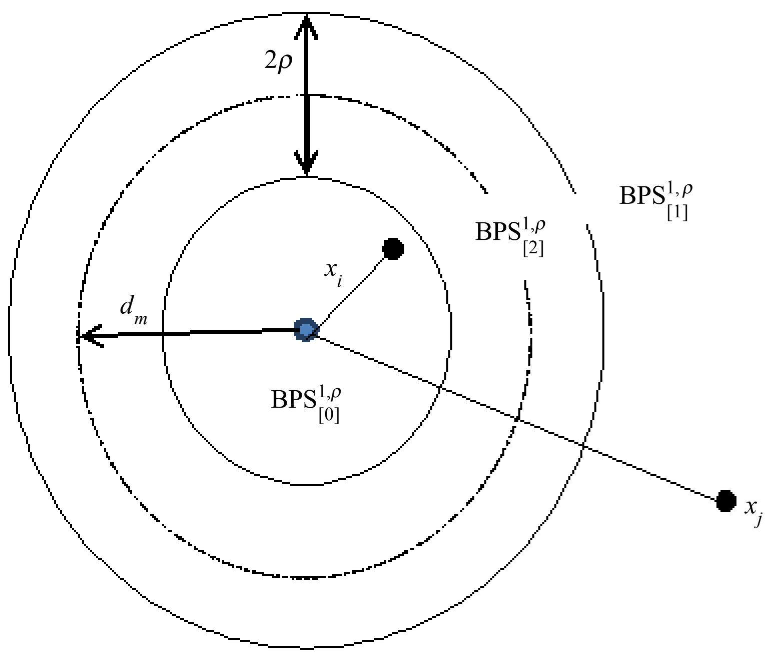

Figure 4. Partioning data by $bps^{1,\rho}(x, x_v)$ ρ - split function

When a range query search radius up to some predefined ρ at most one bucket has to be visited per level plus the exclusion bucket. At the same time, the use of a pivot-filtering strategy significantly cuts the number of distance computations in the accessed buckets.

According with [9] D-index has a several qualitative proprieties, which the most important can be summarized as follows:

• An object is typically inserted at the cost of one block access.

• The number of bucket accesses is maximally $h + 1$, for all response sets, when the distance to the more dissimilar object does not exceed ρ.

• For $r = 0$, the successful search is typically solved with one block access, unsuccessful search usually does not require any accesses.

4. Results

We have implemented a system for the indexing and retrieving of shapes. The software has been developed in visual C++. We used the SQUID database [15] which contains 1100 images of marine creatures, described by their shapes. Furthermore, we have analyzed the performance of D-index using deferent values of parameter ρ in order to choice an adequate value. Next, in intention to verify the effectiveness of our choice of indexing method, we have compared the performance of D-index with other indexing methods on our Data set.

In all our experiments, the search costs are measured in terms of distance computations, and all presented costs are averages obtained by execution queries for 10 deferent query objects with using the same search radius or the same number of nearest neighbors.

4.1 Shape Retrieval

Using a convivial user interface provided by the system, a shape already existing in the database can be used as a query (query by example) by the user. The system retrieves shapes similar in shape to the user query from the database in decreasing order of similarity using the K-nearest neighbor algorithm. Figure-5 shows four example shapes which are used as queries in our experiments. The first ten similar shapes to the query are displayed from left to right and from top to bottom.

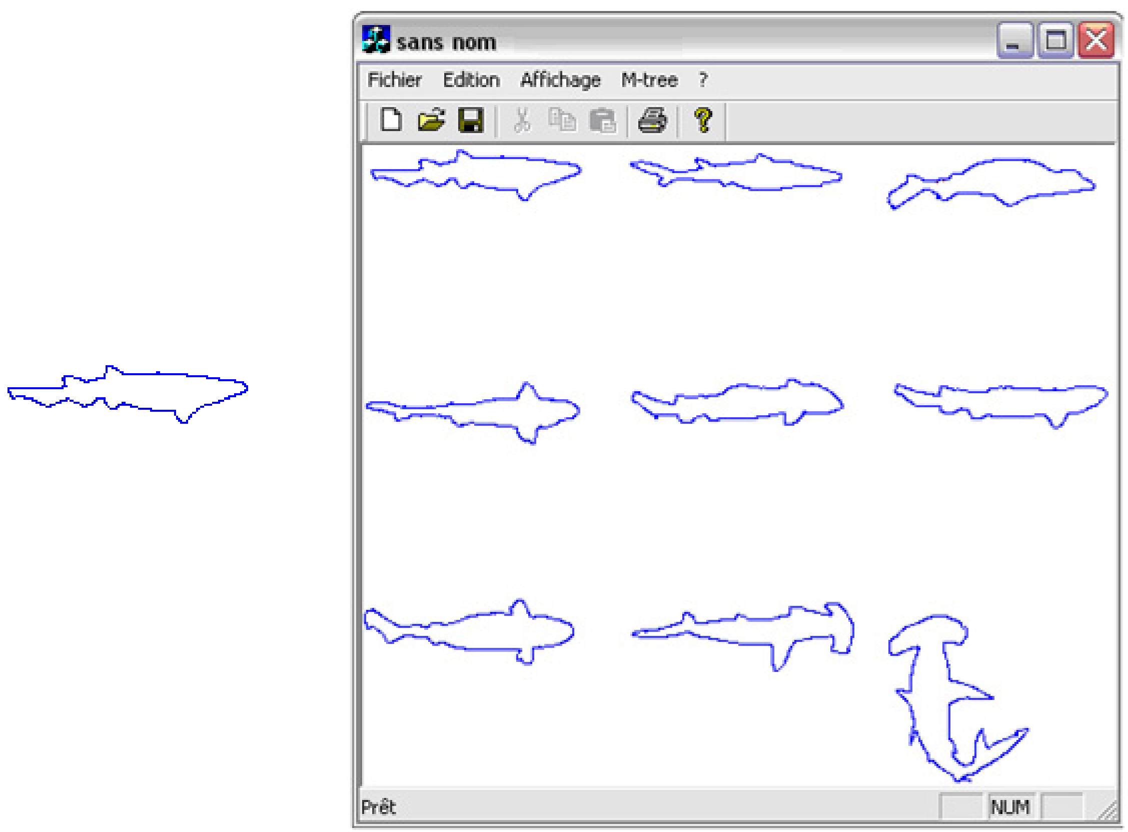

Figure 5. Results of shape Retrieval : (a) Query shape (b) the obtained 9 similar shapes using K-nearest neighbour algorithm. ($K = 9$)

The obtained results are similar to those that a user could find visually.

4.2 System performance evaluation

This group of tests evaluates the relation between the d-index's ρ parameter and the performance of searching in D-index. We have tested this relationship using $\rho = 2, 5, 7$. The results of experiments for the nearest neighbor search are shown in figure 7 while the performance of range search is summarized in figure 6.

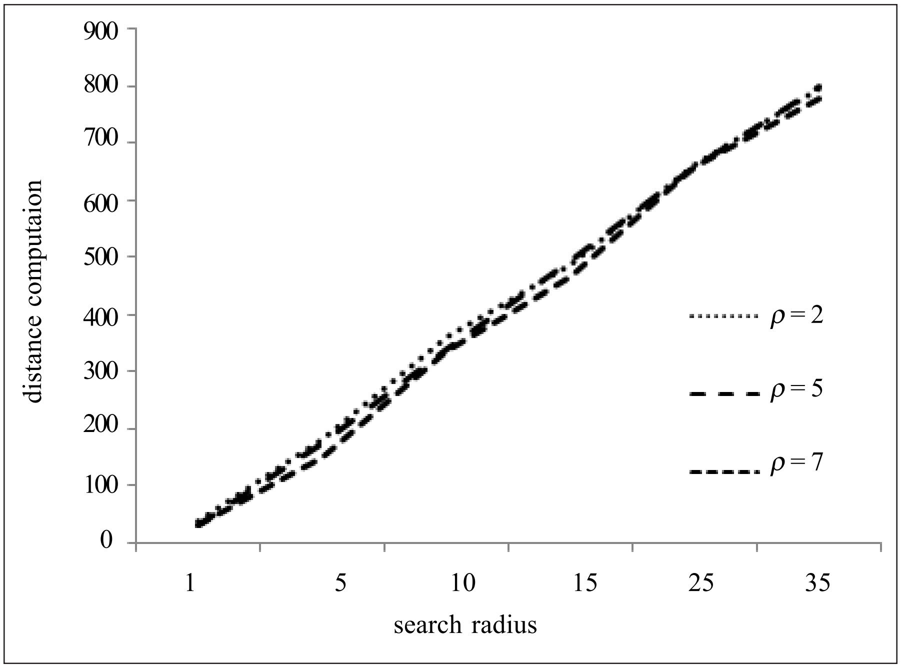

Figure 6. Rang search using different D-index structures

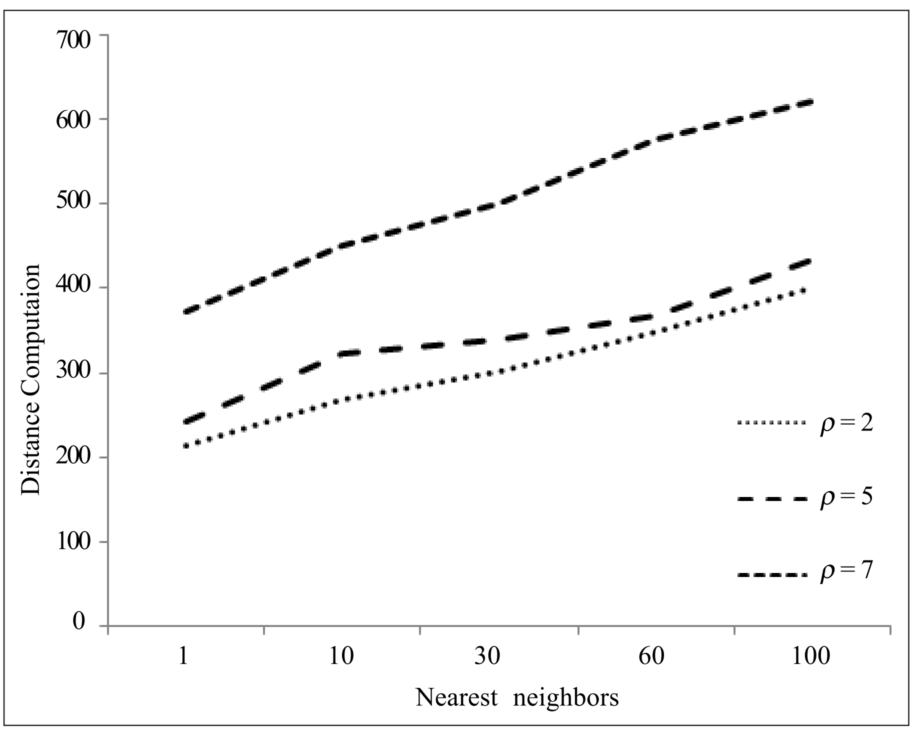

Figure 7. Nearest neighbors search using different D-Index structures

In the search radius, for deferent values of ρ we obtain almost the same performance.However, in the nearest neighbors case-see figure 6- the results imply that the value $\rho = 2$ is preferable, and when we increase the value of ($\rho = 5$, $\rho = 7$) the cost to get the nearest neighbors is increased also. However, the choice of ρ has a significant influence on the performance and the cost of research. The selection of optimized value of ρ is still another research issue that we plan to investigate in the future.

4.3 Performance comparaison

In this test experiment we have compared the performance of D-Index on our databases with other index structures under the same workload. In particular, we considered the MVP-tree [16], SAT [17] and the sequential organization, SEQ. all the four structuresare implemented using the SISAP package [18].

In this experiment test we aimed to compare the similarity search efficiency of the D-Index with the other organizations in our databases. For these experiments, the structure of D-Index was defined by 20 reference objects and 80 buckets. The results for nearest neighbor queries are reported in figure 9. The execution costs for range queries are reported in figure 8.

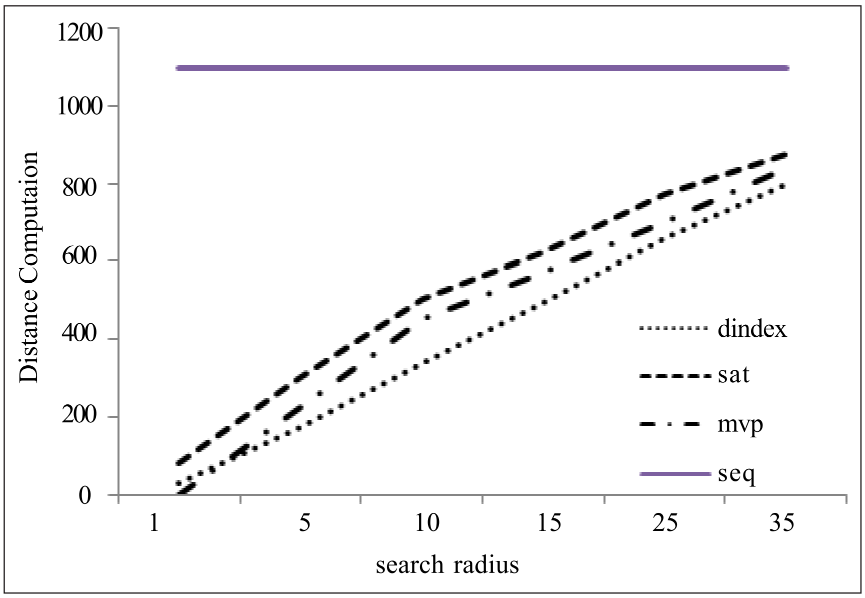

Figure 8. Comparison of the range search efficiency in the number of distance computations

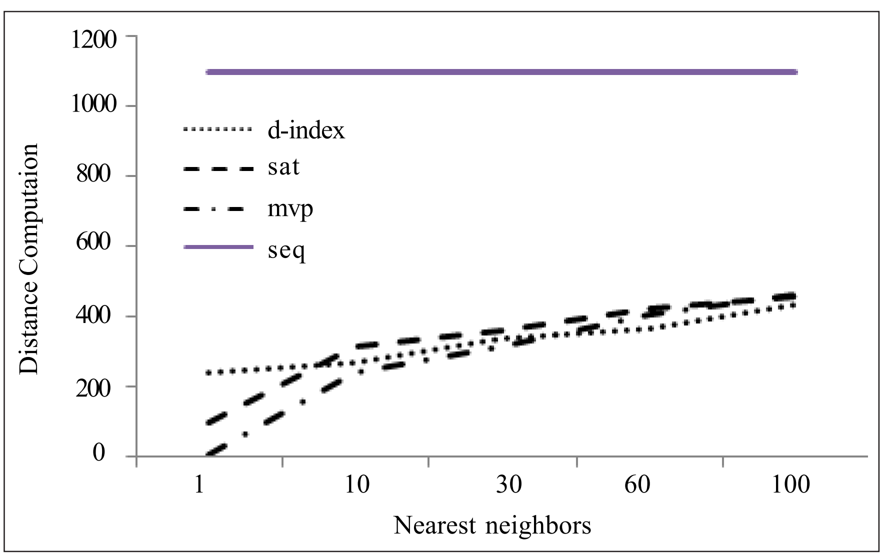

Figure 9. Comparison of the nearest neighbor search efficiency in the number of distance computations

For search query radius we can observe that there is a significant difference between D-index and other structures and the D-index is better than MVP-tree and SAT structures. On the other side the D-index is better than SAT to get more than 30 nearest neighbors and better than MVP-tree to get more than 60 nearest neighbors and better than SEQ for all cases.

5. Conclusion &Perspective

From the results of the previous sections, useful conclusions can be drawn.

We have presented experimental results demonstrating the effectiveness of the Smooth curve decomposition using a shapes database SQUID, the obtained results are similar to those that a user could find visually.

By comparing with other metric access methods in [18], D-index provides a significant effectiveness to indexing and to searching in shape descriptors.D-index structure performance is depends on the choice of ρ parameter.

For increasing performances of D-index, In the future works we will concentrate to developing adequate techniques by proposing heuristic techniques to choice accurate parameters like value set of pivots, number of levels and number of buckets. On the other side we will use D-index with other descriptors like ART [19] and Shape context [20].

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