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Precise shape matching of large shape datasets using hybrid approach

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HIGHLIGHTS

- Formulation of Fourier and approx. IDSC based coarse shape matching.
- Presentation of indexing structure for quick pruning of distant shapes.
- Pruning of distance shape from query using Fourier and approx. IDSC based descriptor and indexing structure.
- Presentation of IDSC-descriptor based fine shape matching.
- Combining FD and IDSC based shape matching for efficiency and accuracy enhancement.

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ABSTRACT

Precise and fast shape matching and retrieval from very large datasets is a challenging task because of the existence of many distortions such as noise, occlusion and affine distortions. In this paper, we aim to propose a time-saving and effective shape matching and retrieval framework, that employs pruning which will enable online shape retrieval from extremely large datasets. First, using a hierarchical tree-based structure supporting parallel processing and efficient feature descriptors, irrelevant shapes are pruned and a subset of shapes relevant to the query is selected, then using more sophisticated feature descriptors, accurate retrieval is performed. Contour representation of an object is considered as most significant visual shape similarity measure by the humans. Using boundary information, we generate two simplified and efficient feature descriptors for fast pruning, and a sophisticated feature descriptor for effective and accurate retrieval. Tests performed on standard datasets unveil that the proposed technique is computationally more efficient than the state-of-the-art techniques while maintaining comparable matching and retrieval performance. Its performance is scalable for huge datasets and is robust against affine transformations, articulations and occlusion.

1. Introduction

In the new age of smart cameras and other digital image capturing devices, the amount of digital images captured nowadays have significantly increased. This accretion has raised an urgent need for general purpose tools for effective and efficient storage as well as retrieval of digital images. Consequently, many researchers have focused on developing sophisticated algorithms for enabling content-based image search. In image shape features are critically important for object modeling and its significance cannot be denied. Various shape matching techniques use these features effectively for content-based similarity measure. Shape matching considers perceptually critical representation of shape and the amount of distance measures that are uneffected by many affine distortions which include noise, articulation, rotation, jag, scale etc. Our main goal in this context, is to propose fast and precise shape matching framework which is resistant to affine rotation, scaling, skew, occlusion and other distortions and give effective online retrieval in the presence of gigantic datasets.

The current state of art for shape matching and recognition is more focused towards the preciseness of shape matching and retrieval systems. Mature shape representation and matching approaches, like [31,2,19,6,28,23,32] etc., are available and can produce outstanding retrieval accuracies in a range of existing articulations like affine deformations, occlusion, noise and articulation. In order to achieve high retrieval accuracies while being in the presence of such deformations, these techniques use complex shape descriptors, complicated distance measures and

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computationally costly similarity techniques. Inevitably, they are time consuming and are computationally expensive. For online retrieval of images timely response is critically as important as accuracy. This paper proposes extraordinarily fast shape matching techniques and parallel processing based indexing structure that uses efficient scalable hybrid approach to quickly trim away shapes which are different from the query shape and then apply time consuming and accurate techniques only on reduced dataset to get precise image extraction results thus meeting the online requirements.

The paper henceforth is organized in the following manner: Section 2 contains review of background material relevant to shape matching. Section 3 presents an overview of the proposed hybrid shape matching framework. In Section 4, we present extremely efficient Fourier descriptor based shape matching to be used for pruning and hybrid shape matching. Sections 5 and 6 present sophisticated *IDSC*-based shape matching and efficient but approximation of *IDSC*-based shape matching respectively. A hybrid shape matching approach for efficient and accurate shape matching is presented in Section 7. In Section 8, experiments are reported to demonstrate the superiority of our proposed approach in contrast with the existing techniques. In the end a discussion and proposals for future work are provided.

2. Related work

An important candidate for content-based image retrieval and recognition is shape descriptors and relative similarity measure. Previously the work that has been done, has attempted to represent these shapes through integral invariants, shape context, curvature, shape signatures, moments etc. In general, we can classify shape portrayal and matching techniques into further two sets: (1) contour-based and (2) region-based approaches. For generating shape representation descriptors contour based approaches employ only boundary information while ignoring all the shape pixels while region based approaches consider all shape pixels.

Majority of contour-based shape features model shape by generating a rather global representation of the contour. Prominent global shape representation approaches include shape signature [17], Fourier coefficients [27,26], differential invariants [12,13], integral invariants [35], shape context (SC) [38,9,8] and shape context including inner distances (*IDSC*) [31]. Belongie et al. [9] proposed SC descriptor, this descriptor uses log-polar coordinates and generates a histogram of contour points using this coordinate system. The sample contour points are selected from contour that are equidistant from one another. Belongie et al. [9] use chi-square distance to compute the distance between SC descriptors whereas Mori et al. [38] employ L^2-norm. Ling et al. [31] developed the Shape Context (SC) descriptor by employing inner distance in place of Euclidean distance. Inner distance is insensitive to significant articulations and variety of complexities in shape, thus resulted in improving the SC. Chi-square distance is used for computing the distance between IDSC descriptors and the final correlation between the *IDSC* descriptors of two shapes is determined using dynamic-programming to accommodate the said temporary relationship between the *IDSC* descriptors. Overall the system yields quality retrieval accuracies in contrast with SC [38] and most other competitors but at high computational cost. Xiao et al. [52,53] applied graph-spectral method that transforms the node correspondent problem into point set alignment by applying Isomap. Extracted shape matching is achieved by finding the correspondence of difference points on the contour. The issue of cospectral nature of the tree structure representation of shapes has been further elaborated in [53].

Much simpler process for shape matching is used global approximation that may require the parameter distance like Euclidean distance [25], Hausdorff distance [15], chi-square distance [31] or a raw point-space distance like Dynamic Time Warping (DTW) [21], and correspondence-based shape matching [38,9,8,31]. Online shape matching in high-dimensional point space is not feasible due to high computational complexity. Some approaches generate localized representations of shapes by dividing contours in different pieces. Piecewise approaches are differentiated based on the criteria used to segment contour into pieces and the feature space employed to model contour segments. Prominent piecewise approaches consist of smooth curve decomposition [10], polygon decomposition [4], and curvature decomposition [18]. [39] proposed a SVM based shape matching where the feature space representation of shapes are generated using gradients of decision functions instead of using edges. These approaches are useful in handling the problem of partially occluded shapes by performing localized shape matching. However, this advantage comes at the cost of complex and inefficient matching. Another problem with piecewise approach is their inability to model global representation of shapes which is critical for accurate shape classification and discrimination.

To overcome the problems associated with exclusive piecewise or global methods, hierarchical methods have been proposed. Hierarchical method captures boundary information at multiple resolutions that range from very coarse (for the global modeling) to very fine levels (for the local modeling) [20,19,36]. Alajlan et al. [2] propose a full multi-scale representation of triangle areas, aiming to capture the local and the global shape information, for the sake of shape matching. Daliri et al. [16] define a rather symbolic descriptor based on Shape Contexts. For handling the existence of noise such as occlusions and articulations, they utilize the known edit distance for the final matching of the string based descriptor.

Another considerably critical affine distortion is rotation, it negatively affects shape matching accuracies and is difficult to handle [25,30]. For achieving rotational invariant shape matching, a variety of approaches have been proposed. Some of these approaches [14,40] employ rotational invariant features such as curvature and centroid distances based features, ratio of perimeter to the area, convexity, circularity and so on. These features give a very coarse representation of shape thus compromising the accuracy. There exists a variety of approaches that use 1D time series as shape representation [1,48,11].

Rotation invariance is achieved by some of these approaches [11] by the selection of considerably fewer starting points (alignment according to the major axis) in order to gain 1D time series depiction of the 2D shape. However, such alignments are considerably erratic especially when there is a lack of well established major-axis and slight variation in shape can have prominent effect on rotation alignment. Likewise, in order to define the true alignment of shape some researchers proposed to use brute-force search on all possible rotation arrangements available. [25,1,48]. For achieving all possible rotation alignments, one contour has to be shifted n times ($n \gg 100$) where n is the number of contour points. This approach will result in accurate rotation invariant system but will compromise the efficiency of the mentioned content-based image search and retrieval systems.

Previous research such as [23,32,31,2,19,6,28,50,33,49] has focused mainly on accuracy of shape matching techniques while giving less attention to the efficiency problem. These approaches would not at all be feasible to be utilized in real-life scenarios specially when having such large shape datasets. The problem of scaling of shape search to comparatively large databases still exists with most of existing shape matching methods. Recent research work like [38,25,34], discusses the scalability issue of generally large datasets. Mori et al. [38] propose two pruning techniques

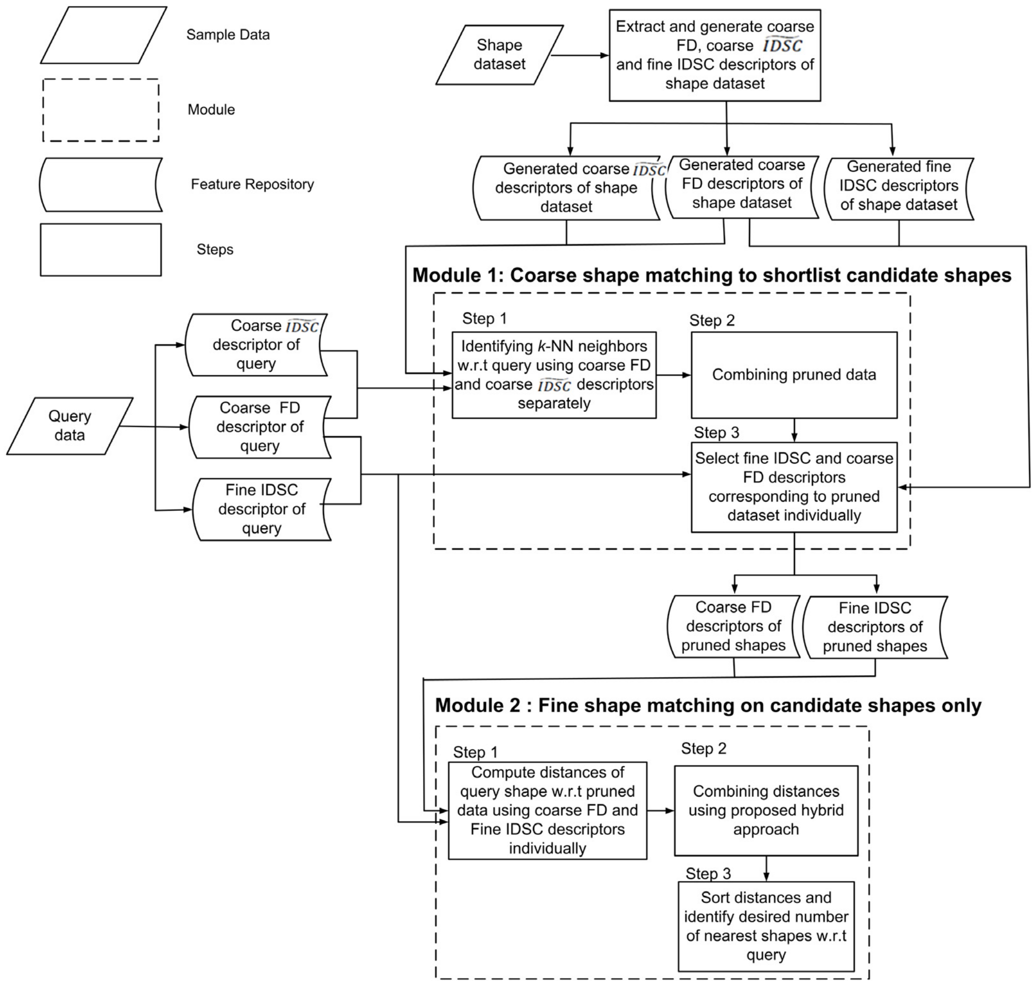

Fig. 1. Overview of our proposed hybrid shape matching framework.

in order to address the efficient problem of shape matching from these large shape datasets. The first pruning approach utilizes vector quantization on the SC descriptor and to replace each shape context with its corresponding cluster ID. In second pruning approach, a subset of SC descriptors was selected randomly. The main flaw of this particular approach is that it does not guarantee uniformity such as whether SC descriptors are generated roughly at about similar location on shapes which belong to many different classes that results in inaccurate matching results. Keogh et al. [25] tried scaling their shape matching approach to the large datasets by proposing a wedge-based technique. This approach works on high dimensional time series model of shape contour and by applying brute force approach for the named rotational invariance. All these factors result in relatively higher computational complexity. Lowe et al. [34] propose a $k-d$ tree based indexing structure particularly for efficient shape matching by using the "Best-Bin-First" based algorithm. Tan et al. [47] and Grauman et al. [24] suggested R-tree and Nested R-trees approach for the indexing feature vector dependent shape representation. Inverted files based indexing is also presented for indexing of a high dimensional sparse vector based shape representation [42,45].

3. Overview of proposed shape matching framework

Accurate and efficient shape matching and extraction from large datasets, in the existence of distortions like noise, occlusion and affine distortions, is a challenging task. Fig. 1 presents an overview of our proposed hybrid shape matching framework to cater for this challenge. The proposed approach is composed of two main modules: (1) efficient but approximate coarse shape matching to quickly prune candidate subset of shapes from the dataset (2) accurate but time consuming fine shape matching using only pruned subset of candidate shapes w.r.t. query. The proposed approach employs coarse shape descriptors to support approximate but efficient shape matching and fine shape descriptors to support accurate but time-consuming shape matching. The coarse descriptors employed in proposed approach include Fourier Descriptors (*FD*) and approximate Inner Distance based Shape Context descriptors ($\widetilde{IDSC}$). Although multiple fine descriptors may be used, the one employed in the proposed approach is actual Inner Distance based Shape Context (*IDSC*).

Given a query shape, we generate these descriptors for the query and use it for coarse and fine shape matching. The coarse shape matching and pruning module comprises of three major steps employing coarse shape descriptors. In step 1, we perform *k*-NN search separately using FD descriptor and approximate $\widetilde{IDSC}$ descriptor. Use of multiple coarse descriptors with different modeling strategies enables modeling the shape from different perspective resulting in better results of hybrid coarse shape matching thus resulting in reduction of false negatives. Extremely efficient coarse shape matching is enabled by employing proposed indexing and distributed/parallel beam search based retrieval approach. The *k*-NN results obtained separately from FD and IDSC based shape matching are combined in the second step to obtain small subset of candidate shapes that are similar to query shape. In the third step, fine shape descriptors corresponding to the

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candidate shape subset are extracted to be used in the next module of fine shape matching on a very small subset of candidate shapes w.r.t. query shape. The module of fine level shape matching is further composed of three steps. In step 1, we compute the distance of query shape with the shapes in pruned dataset using *FD* and *IDSC* descriptors separately. These distances are then combined using the proposed hybrid approach in step 2. In step 3, the required number of nearest neighbors w.r.t. query is then identified by sorting the hybrid distance and selecting the required number of nearest shapes. The proposed framework is expected to increase the overall accuracy of the selected fine shape matching technique and also significantly improving its efficiency.

4. Shape matching based on Fourier descriptors using hierarchical indexing structure

In this section, we present an exceptionally efficient technique for shape matching. This approach uses Fourier descriptors as shape features. The Fourier descriptor based shape matching is used for two important reasons (i) The shape matching using low dimensional Fourier descriptor is extremely efficient and it can be integrated in hierarchical tree based indexing and retrieval scheme for quickly removing distant shapes and also identifying a candidate list of approximately similar shapes w.r.t. query. Accurate but inefficient shape matching can than be applied using the pruned set of candidate shapes. (ii) Fourier descriptors can be fused in a hybrid framework (proposed later) with complex shape matching approach to enhance the resultant classification/retrieval accuracy.

4.1. Fourier descriptors based shape matching

Fourier descriptors based shape matching (FDSM) exploits the boundary information by considering it as a time series thus providing a global contour based shape representation. Object contour $C(O)$ of shape is first extracted using Moore–Neighbor tracing algorithm [22] and is represented as:

$$C(O) = \{(x_1, y_1), (x_2, y_2), (x_3, y_3), \ldots, (x_n, y_n)\} \tag{1}$$

where n is the number of contour points. 1D time series representation of shape from 2-D contour is obtained by the calculation of the distance of each point from the mean point(centroid) as:

$$CD_t = \{\sqrt{((x_t - x_c)^2 + (y_t - y_c)^2)}\} \quad t = 1, 2, 3, 4, \ldots, n \tag{2}$$

where *CD* is centroid distance based 1-D time representation of shape and x_c is the average of all the contour points. To deal with scale invariance, *CD* is thus normalized as:

$$\ddot{CD}_t = \frac{CD_t - \mu}{\sigma} \quad t = 1, 2, 3, 4, \ldots, n \tag{3}$$

where μ and σ are the mean and standard deviation of *CD* respectively. Depiction of extracting 1-D time series representation from shape is presented in Fig. 2.

Discrete Fourier Transformation (DFT) is then applied to produce compress feature space illustration of high-dimensional $\ddot{CD}$ based time series representation. The complex DFT coefficients of $\ddot{CD}$, referred to as $\overline{CD}$, are computed as:

$$\overline{CD_f} = \frac{1}{\sqrt{n}} \sum_{i=1}^{n} \ddot{CD}_i \exp(-j2\pi fi/n) \quad f = 1, 2, 3, \ldots, n \tag{4}$$

where $j = \sqrt{-1}$ and $\overline{CD_f}$ equal to complex numbers while ruling out $\overline{CD_0}$ which is real and represents the mean value of $\ddot{CD}$. We ignore $\overline{CD_0}$ as $\ddot{CD}$ is *z*-normalized and its mean will always be zero and hence useless. To ignore high frequency noise related information while retaining low frequency shape orientation information, we truncate the DFT sequence is trimmed after m terms, $f = 1, \ldots, m-1$. Resultant feature vector includes $2(m-1)$ terms (along with real and imaginary parts). Moreover, the DFT coefficients $\mathbf{F}_{DFT}$ dependent feature vector representation of the given shape are attained as: a_i and $\widehat{a_i}$ are the real and imaginary parts of $\overline{CD}$. The shapes may also be represented in the given coefficient feature space by a $2(m-1)$ dimensional vector of DFT coefficients $\mathbf{F}_{DFT}$, where

$$\mathbf{F}_{DFT} = [a_1, \widehat{a}_1, \ldots, a_{m-1}, \widehat{a}_{m-1}] \tag{5}$$

where a_i and $\widehat{a_i}$ are the real and imaginary parts of $\overline{CD}$. The above mentioned feature space representation may be properly maintained for shape matching of two different contours that are said to be rotationally aligned. However, this case is very rare. Our rotational invariance approach is inspired from [25] with a difference that instead of rotating two shapes in accordance with all possible arrangements of two shapes that are computationally very extravagant, we propose to rotate the two shapes according to some selected points known as critical points on two contours and search to look for the calibration which gives the minimum stated distance between feature space representation of the stated two contours. These critical points are identified through determining local maxima in 1D *CD*-space representation of shape. Fig. 3 depicts the identification of critical points on the contour.

Let $G = \{g_1, g_2, g_3, \ldots, g_q\}$ be a *CD*-space representation of shape, given a set of nc_G critical points $C = \{c_1, c_2, \ldots, c_{nc_G}\}$ is identified using G. Rotational invariance is achieved by expansion of G into a matrix $\mathbf{G}$ of nc_G a form of time series as:

$$\mathbf{G} = \begin{bmatrix} g_{c_1}, \ldots, g_{q-1}, g_q, g_1, \ldots, g_{c_1-1} \\ g_{c_2}, \ldots, g_{q-1}, g_q, g_1, \ldots, g_{c_2-1} \\ \vdots \\ g_{c_{nc_G}}, \ldots, g_{q-1}, g_q, g_1, \ldots, g_{c_{nc_G}-1} \end{bmatrix}. \tag{6}$$

Each row in matrix $\mathbf{G}$ corresponds to the time series representation of contour in *CD*-space that is aligned in consistent with one of the stated critical points. We pad our described matrix $\mathbf{G}$ with the reversal of particularly all of the time series, to counter any existing mirrored images, as:

$$\mathbf{G} = \begin{bmatrix} g_{c_1}, \ldots, g_{q-1}, g_q, g_1, \ldots, g_{c_1-1} \\ g_{c_2}, \ldots, g_{q-1}, g_q, g_1, \ldots, g_{c_2-1} \\ \vdots \\ g_{c_{nc_G}}, \ldots, g_{q-1}, g_q, g_1, \ldots, g_{c_{nc_G}-1} \\ g_{c_1-1}, \ldots, g_1, g_q, g_{q-1}, \ldots, g_{c_1} \\ g_{c_2-1}, \ldots, g_1, g_q, g_{q-1}, \ldots, g_{c_2} \\ \vdots \\ g_{c_{nc_G}-1}, \ldots, g_1, g_q, g_{q-1}, \ldots, g_{c_{nc_G}} \end{bmatrix}. \tag{7}$$

Let $\mathbf{H}$ be a feature matrix representation of yet another shape having nc_H critical points. The rotational invariant distance between shapes G and H is described as:

$$Dist_{FD}(\mathbf{G}, \mathbf{H}) = \min_{1 \le i \le nc_G} \min_{1 \le j \le nc_H} (\|DFT(G_{c_j}), DFT(H_{c_i})\|) \tag{8}$$

where $DFT(\cdot)$ is a DFT based dimension reducing function and $\|\cdot, \cdot\|$ is the given Euclidean distance. Time complexity analysis of executing a query on a shape database by using FDSM algorithm is $O(2{*}nc_G{*}nc_H{*}m{*}N)$ where nc_G and nc_H are the number of existing critical points, m is the length of feature vector representation of shape and N is the total number of shapes in dataset. The total number of critical points barely surpass 15 even for complicated shapes and the value of m is according to the order of 8 to 32. As a result, the overall complexity of FDSM algorithm reduces to $O(N)$.

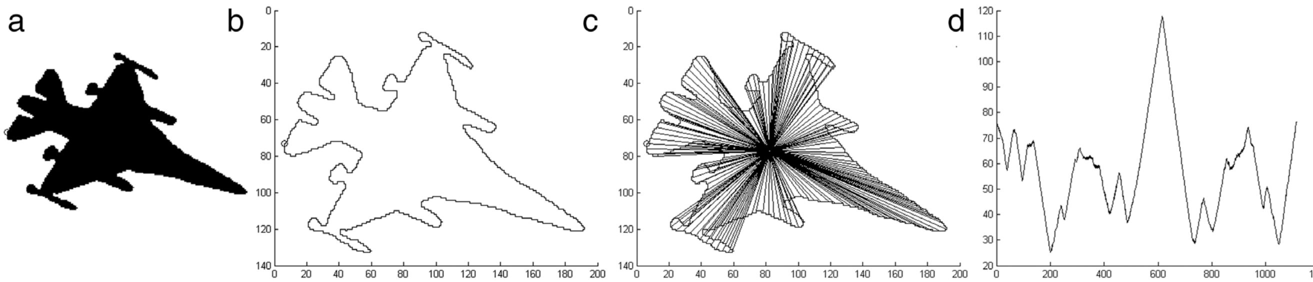

Fig. 2. Extracting 1-D time-series representation of shapes. (a) Original image with 2D shape. (b) C space representation with 'o' marking the initial point. (c) Projection of contour from 2D C-space to 1D CD-space. (d) CD-space representation of shape.

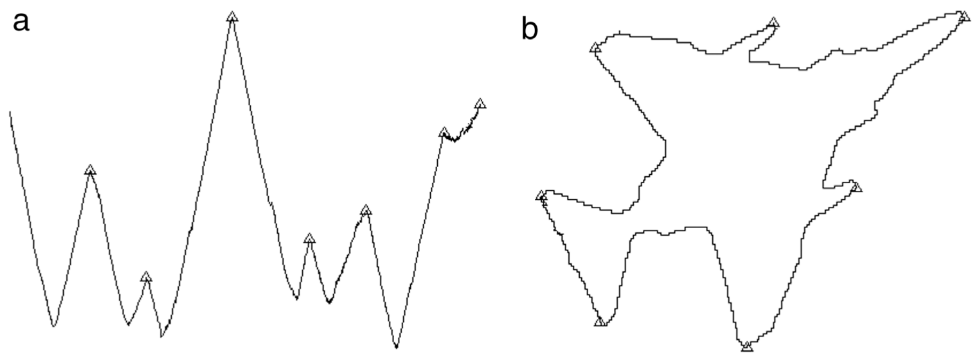

Fig. 3. Estimating critical points through the use of local-maxima heuristic. '△' marks highlight the extracted critical points in (a) CD-space (b) contour-space representation.

4.2. Hierarchical tree-based indexing

Although, FDSM is an extremely efficient approach for shape matching, we further improve its scalability to larger datasets by efficiently trimming out the distant shapes and identifying lists of similar shapes which may include k-nearest neighbors of the query. This process, while speeding up the FDSM, enables very complex and slow shape matching approaches to be applied on the extracted subset of shapes, thus making them feasible to be applied in case of a very large dataset available. We present an approach to create index of shape dataset. The suggested technique for creating index of shape-database is a tree-based indexing approach that performs hierarchical quantization and determines certain number of groupings from the subset of shapes at each level. The recursive clustering of shapes continues until a stopping criterion is reached. Each group of shapes is then represented through a node present in the tree which is basically a generalized representation of shapes within the group. The proposed hierarchical tree-based indexing algorithm is comprised of the following steps:

(1) Firstly, low dimensional matrix of DFT coefficient based representation of shapes is generated by applying dimensionality reducing function on each time series in the matrix-based representation ($\mathbf{G}$) of shapes in dataset DB as shown in Eq. (5).
(2) Then Learning Vector Quantization (LVQ) network with $3 * b^*$ number of obtained output neurons where $b*$ is the number of groupings that we wish to define is initialized. The number of given input neurons is equivalent to the size of feature vector representation of a single alignment of contour.
(3) DFT-based feature space representation of the original arrangement of shapes is extracted, mean (μ) and covariance (Σ) are also estimated. Weight vectors W_i (where $1 \leq i \leq \#_{output}$) are initialized from the $PDF\ N(\mu, \Sigma)$.
(4) Winning node is identified k (indexed by c) as:

$$Dist_{FD}(W_c, \mathbf{G}) \leq Dist_{FD}(W_k, \mathbf{G}) \quad \forall k. \tag{9}$$

(5) LVQ network is updated by tuning the weight vector W_c of the winning output neurons c as:

$$W_c(t+1) = W_c(t) + \alpha(t) Dist_{FD}(W_c, \mathbf{G}) \tag{10}$$

where t is the index of training cycle and $\alpha(t)$ is the rate of learning of LVQ which is updated after each iteration as:

$$\alpha(t) = 1 - e^{\frac{2(t-\acute{t})}{\acute{t}}} \tag{11}$$

where $\acute{t}$ is the maximum number of training iterations.
(6) Loop through steps 4 and 5 for $\acute{t}$ iterations.
(7) Output neurons with zero membership are filtered.
(8) The nearest pair of output neurons is merged (indexed by (a, b)) as

$$W_{ab} = \frac{mW_a + nW_b}{m+n} \tag{12}$$

where

$$(a, b) = \underset{(i,j)}{\arg\min}\, [(W_i - W_j)^T (W_i - W_j)]^{\frac{1}{2}}$$
$$\forall i, j \wedge i \neq j \tag{13}$$

and m, n are the total number of samples corresponding to output neuron stated as a and b respectively.
(9) Step 8 is repeated until there are b^* number of output neurons.
(10) b^* nodes are generated and are represented by Γ, in the hierarchical tree and set:

$$\begin{aligned} &\Gamma_i \cdot \overline{W} = W_i \\ &\Gamma_i \cdot max = \max_{\forall \mathbf{G} \in \Gamma_i} (Dist_{FD}(\Gamma_i \cdot \overline{W}, \mathbf{G})) \quad \text{for } i = 1, \ldots, k \\ &\Gamma_i \cdot mean = \sum_{\forall \mathbf{G} \in \Gamma_i} (Dist_{FD}(\Gamma_i \cdot \overline{W}, \mathbf{G}) / |\Gamma_i|) \\ &\Gamma_i \cdot std = \sum_{\forall \mathbf{G} \in \Gamma_i} (Dist_{FD}(\Gamma_i \cdot \overline{W}, \mathbf{G}) - \Gamma_i \cdot mean) / |\Gamma_i| \end{aligned} \tag{14}$$

where $|\Gamma_i|$ is the membership count of node Γ_i, $\Gamma_i \cdot \overline{W}$ is the generalized representation of group of shapes indexed by

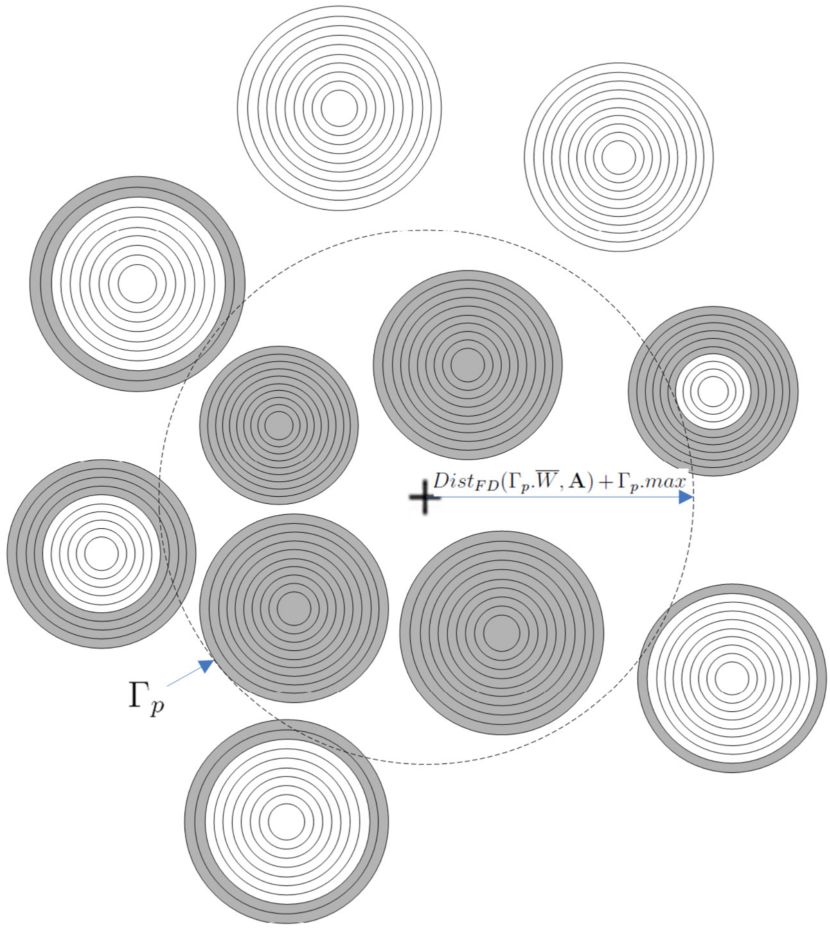

Fig. 4. Depiction of proposed pruning mechanism using ring-based orientation of leaf nodes.

Γ_i, $\Gamma_i \cdot max$ and $\Gamma_i \cdot std$ are the max and standard deviation of the distance of feature vector representation of member shapes from $\Gamma_i \cdot \overline{W}$ respectively. The node also stores the IDs of shapes that are identified as members of a given node. To further enhance pruning power, member shapes of a given node are additionally placed into $i = 1, \ldots, p$ bins (depicted as rings in Fig. 4). There bins are developed based on the distance of feature vector representation of shapes from node center, represented by $\Gamma_i \cdot \overline{W}$. Generated nodes are then added as the descendant of the corresponding parent node in the index tree.

(11) Subset of nodes, are then identified referred to as $\widehat{\mathbf{\Gamma}}$, whose count of membership is more than a cluster membership threshold κ as:

$$\widehat{\mathbf{\Gamma}} = \{\Gamma_i \in \mathbf{\Gamma} \| \Gamma_i| > \kappa\} \quad \forall i. \tag{15}$$

(12) The stability of indexing process is then validated.

(13) The indexing process is terminated if it is stable ($\widehat{\mathbf{\Gamma}} = \{\}$). Otherwise, select subset of shapes indexed by a node from $\widehat{\mathbf{\Gamma}}$ and the process is repeated to generate b* groupings from the selected subset of shapes.

4.3. Retrieval using generated index

In this section, we propose our retrieval algorithm, known as Distributed Beam Search (DBS), which employs generated indexing structure to look for k-NN of the query shape while guaranteeing no false dismissals. Instead of selecting a single child node at a given depth level, DBS selects and evaluates multiple child nodes which enables our approach to explore all possible nodes that may be indexing one of the related shapes desired to be present in the k-NN results w.r.t. query shapes. Retrieval of k-NN using our proposed DBS approach is comprised of steps given below:

(1) Feature space representation of the query dependent shape is generated ($\mathbf{Q}$) as specified in Eq. (7).

(2) The list of candidate nodes are initialized $\mathbf{\Gamma}$ with nodes existing at depth 0 of the tree.

(3) The nodes are then arranged in $\mathbf{\Gamma}$ in an increasing order with respect to the distance of their comprehended feature space representation from $\mathbf{Q}$.

(4) Extract first subset of related nodes w.r.t. query as:

$$\mathbf{\Gamma}_\iota = \Big\{\{\Gamma_1, \Gamma_2, \ldots, \Gamma_p\} \in \mathbf{\Gamma} | \sum_{i=1}^{p} \Gamma_i.count \geq k \wedge \sum_{i=1}^{p-1} \Gamma_i.count < k\Big\} \tag{16}$$

where p is known to be an index of farthest node from $\mathbf{Q}$ in $\mathbf{\Gamma}_\iota$ and k is the number of closest neighbors that we actually want to retrieve w.r.t. query shape.

(5) Select another subset of nodes from $\mathbf{\Gamma}$ as:

$$\mathbf{\Gamma}_\jmath = \{\Gamma_i \in \mathbf{\Gamma} \parallel (Dist_{FD}(\Gamma_i \cdot \overline{W}, \mathbf{Q}) - \Gamma_i \cdot max) \leq (Dist_{FD}(\Gamma_p \cdot \overline{W}, \mathbf{Q}) + \Gamma_p \cdot max)\} \quad \forall i. \tag{17}$$

This subset ensures that we do not miss on any shape that has a chance to be part of k-NN results in accordance with the query using sequential shape matching.

(6) Set $\mathbf{\Gamma} = \mathbf{\Gamma}_\iota \cup \mathbf{\Gamma}_\jmath$.

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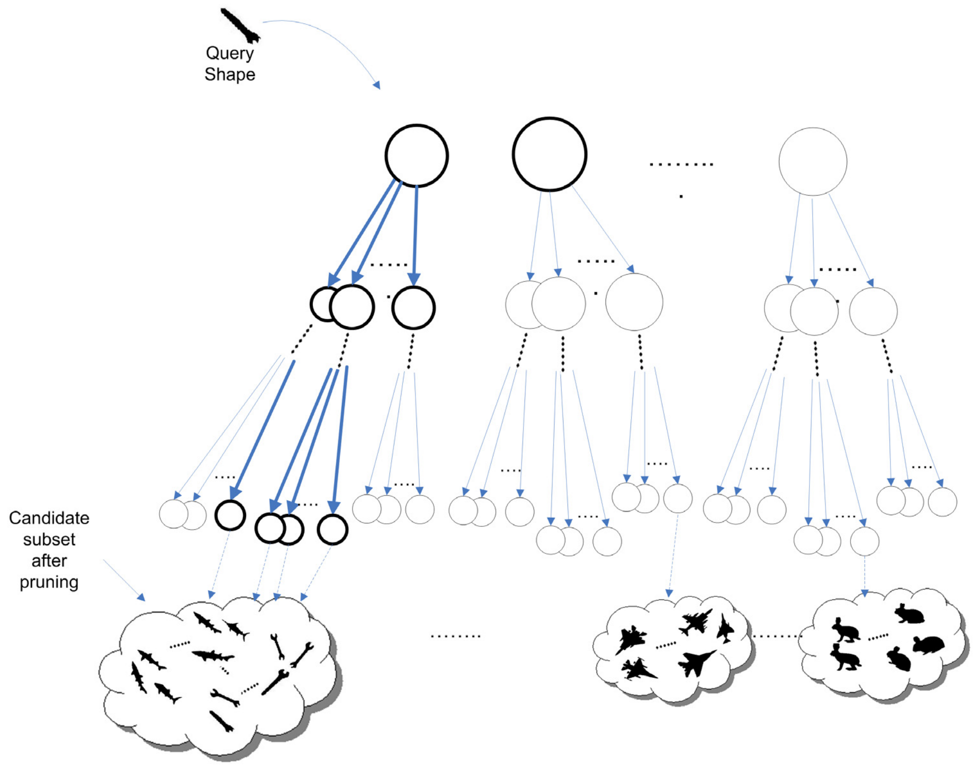

Fig. 5. Depiction of DBS to perform k-NN query using tree-based indexing structure.

(7) Replace non-leaf nodes in $\boldsymbol{\Gamma}$ with its corresponding child nodes. Iterate through steps 3 to 7 till there are no non-leaf nodes in $\boldsymbol{\Gamma}$.

(8) Select all possible shapes that are indexed by those nodes in $\boldsymbol{\Gamma}$ fulfilling the following criteria:

$$Dist_{FD}(\Gamma_i \cdot \overline{W}, \mathbf{Q}) \leq (Dist_{FD}(\Gamma_p \cdot \overline{W}, \mathbf{Q}) + \Gamma_p \cdot max) \quad \forall i \in \boldsymbol{\Gamma}. \tag{18}$$

(9) Select only subset of shapes indexed by nodes in $\boldsymbol{\Gamma}$ not fulfilling the criteria as specified in Eq. (18). Those shapes are selected which belong to the exterior ringlets around the nodes whose distance from $\mathbf{Q}$ is smaller than $(Dist_{FD}(\Gamma_p \cdot \overline{W}, \mathbf{Q}) + \Gamma_p \cdot max)$. Depiction of retrieval process using presented indexing structure is shown in Fig. 4. The query shape in a given state space is represented as '+' marker in Fig. 4. Rings within nodes represent bin and radius of nodes represents the maximum distance of member shapes from generalized feature space representation of the corresponding node. The shapes shown in shaded region of state space is chosen for sequentially matching with query shape.

(10) Perform k-NN query using subset of shapes selected in steps (8) and (9), referred to as DB_{pruned}, as:

$$k - NN(\mathbf{Q}, DB_{pruned}, k) = \{C \in DB_{pruned} | \forall \mathbf{R} \in C, \mathbf{S} \in DB_{pruned} - C, Dist_{FD}(\mathbf{R}, \mathbf{Q}) \leq Dist_{FD}(\mathbf{S}, \mathbf{Q}) \wedge |C| = k\} \tag{19}$$

where $\mathbf{S}$ and $\mathbf{R}$ are feature space representation of shapes in DB_{pruned}.

Process of retrieval using proposed indexing mechanism is highlighted in Fig. 5. The membership count of each node is depicted by the radius of each node. Parsing the tree through a single branch for shape retrieval and selecting only one node at each level will result in ignoring related shapes that are indexed by some other nodes at those levels. This might have resulted in false dismissals in the search results. DBS solves this problem by performing multi-branch parsing and selecting all nodes with the finest of chances to contain the shapes of the desired result.

5. *IDSC* based shape matching

This section presents a shape matching approach on the basis of Shape Context by the use of Inner Distance (*IDSC*) as presented in [31]. *IDSC* descriptors are considered to be state-of-the-art shape descriptors that generate sophisticated representation of shapes. However, matching using *IDSC* descriptor, as presented in [31], is inefficient. We have selected *IDSC* descriptors to be used in hybrid shape matching framework with Fourier descriptors. Fourier descriptor based shape matching is employed to quickly retrieve certain number of nearest neighbors. Inefficient but accurate shape matching using *IDSC* descriptors is then employed considering only selected subset of candidate shapes. The *IDSC* dependent approach is in short described here for the completeness of text and its relationship with Approximate *IDSC* ($\widetilde{IDSC}$) based approach presented in next section. Original shape context (SC) descriptor as given in [9] models that complete shape according to a specific point using oriented direction and the distance bins. Euclidean distance is used to determine the distance between the two points. Ling et al. [31] improved the shape descriptor by producing the bins through the use of inner distance and giving definition to the orientation as the tangential direction at the initial point of shortest path. It is provided that a time series representation of shape contour, as stated in Eq. (1), a set of fixed number of equidistant sample points ns, are extracted on the contour. Suppose $SP = \{sp_1, sp_2, \ldots, sp_{ns}\}$ is the set of sample points on the contour, interior distance based shape context ($IDSC_i$) at the sample point sp_i is given as:

$$IDSC_i(k) = \#\{sp_j : sp_j - sp_i \in bin(k) \; \forall j \wedge i \neq j\} \tag{20}$$

where bins are evenly distributed in the log-polar space.

Consider Q and R to be the query shapes and shapes from dataset to be sets of available sample contour points $q_1, q_2, \ldots, q_{ns}$ and $r_1, r_2, \ldots, r_{ns}$ respectively. Let $IDSC^Q$ and $IDSC^R$ be the sets of $IDSC$ descriptors that are produced on sample contour points of the shape Q and R, as stated in Eq. (1). The described distance matrix in between the $IDSC$ descriptors which uses χ^2 statistics and computation is as follows:

$$DM_{ij} = \frac{1}{2} \sum_{1 \le k \le K} \frac{(IDSC_i^Q(k) - IDSC_j^R(k))^2}{IDSC_i^Q(k) + IDSC_j^R(k)} \tag{21}$$

where $IDSC_i^Q$ and $IDSC_j^R$ are the $IDSC$ descriptor of q_i and r_j respectively and k is the stated number of total histogram bins used for creating $IDSC$ descriptors. Then dynamic programming function is used to calculate distance between shapes to search the correlation regarding sets of points on contour by utilizing the sequential information of the known contour. Dynamic Programming [7,41] has been commonly used for finding interrelation between the temporary data.

Previously mentioned feature space representation and matching presumes that the two contours are aligned in a rotational manner which is scarce. The original $IDSC$-based shape matching approach aims to conquer rotational invariance by random selection of certain number of initial starting points for contour arrangement. Instead, we then align the two given shapes by employing critical points based arrangement techniques as specified in Section 4.1. Here, we use earliest possible removal, as discussed in [25], for reducing the computational complexity in order to achieve the rotational invariance in shape matching. The basic initiative leading to early removal is that we eliminate the computation of the said distance between two shapes for an available mentioned arrangement if it gets greater than the distance already computed for another arrangement of the shape.

6. *IDSC* based approximate shape matching

Now in this section, we propound for generation of an approximate representation of $IDSC$ descriptors ($\widetilde{IDSC}$) for rough but yet efficient enough shape matching. The main incentive behind generation of second coarse representation of shapes along with Fourier coefficients is to use descriptors that generate approximate modeling of shapes from different perspective. The pruning results of these two coarse shape matching approaches will be combined to have a refined pruned subset of shapes. Fine, accurate and more tedious complex shape matching approaches can then be used on the shapes, which are known to be as k-NN according to query shapes using coarse matching.

We now find a set of critical points along the contour through the combination of the critical points which were obtained by the use of polygon decomposition approach from the already mentioned group of fixed number of sample points ns on the shape contour [51] and the refinement of the critical point detection approach as outlined in Section 4.1. Now we aim to find both local minima and maxima along the centroid distance area which is to be included in the given set of critical points. $IDSC$-based shape descriptors are created when not just on the critical points but also all given the sample points along the contour are taken into account. Let us consider Q and R to be the two shapes which are being represented by a set of critical points $\{q_1, q_2, \ldots, q_{nc_Q}\}$ and $\{r_1, r_2, \ldots, r_{nc_R}\}$ where nc_Q and nc_R are the number of critical points as known for the shapes Q and R respectively. $IDSC$ descriptors are generated on identification of the critical points of the shape Q and R, using Eq. (20) and are known as $\widetilde{IDSC}$.

Let $\widetilde{IDSC}^Q$ and $\widetilde{IDSC}^R$ be a described set of $IDSC$ descriptors which are generated on the given critical contour points of the given query shape Q and the given sample shape R from the given dataset. For computation of distance between two $\widetilde{IDSC}$ descriptors, we tend to use Euclidean distance as it is quite efficient. Since aim is not generating $\widetilde{IDSC}$ descriptors on all the points of the contour, so every descriptor on the query shape will give an approximately fitting match on similarity but distorted shapes due to noise, affine transformation and occlusion. In order to solve this problem and to contribute in the distance measure only a subset of $\widetilde{IDSC}^Q$ descriptors is selected to search for a fitting match with the $\widetilde{IDSC}^R$ descriptors. That is to say, the distance between $\widetilde{IDSC}$ descriptors of query shape Q and sample shape R is calculated as stated:

(1) Distance of each $\widetilde{IDSC}$ shape descriptor Q is calculated with its closest $\widetilde{IDSC}$ descriptor of shape R as:

$$D_{QR}(i) = \min_{\forall j} \|\widetilde{IDSC}_i^Q, \widetilde{IDSC}_j^R\| \quad \forall i \tag{22}$$

where $D_{QR}(i)$ is distance of ith $\widetilde{IDSC}$ descriptor on shape Q according to $\widetilde{IDSC}$ descriptors of shape R.

(2) Sort D_{QR} in the ascending order.

(3) The computation of distance between shape Q and R is stated as:

$$Dist_{\widetilde{IDSC}} = \sum_{i=1}^{p} \widehat{D_{QR}} \tag{23}$$

where $\widehat{D_{QR}}$ is the sorted distance set while p is the number of matches that are closest to descriptors of Q with R. Value of p is calculated in relation nc_Q as:

$$p = \lceil 0.4 * (1 - (nc_Q - min_{nc})/(max_{nc} - min_{nc})) + 0.3 \rceil \tag{24}$$

where min_{nc} and max_{nc} are the approximate values of minimum and maximum number of the total critical points on shape contours from the given shape dataset.

7. Hybrid shape matching

In this section, we are going to propose hybrid shape matching approach that integrates the shape matching techniques, as presented in Sections 4–6. For large datasets, we build a brief list of candidate shapes which hold some chances for making k nearest matches as wanted by the client while pruning shapes that are irrelevant i.e. far from the query shape. For quickly pruning distant shape we use $\widetilde{IDSC}$ and FD based roughly proposed shape matching using presented tree-based indexing structure. More complex, slow and precise shape matching approaches, based on combination of $IDSC$ and FD based shape descriptors are then applied on a subset of the shape dataset whose identity was known while coarse matching phase was taking place. The suggested hybrid shape matching algorithm consists of following steps:

(1) FD, $IDSC$ and $\widetilde{IDSC}$ based feature space representation of the given query shape as discussed in Sections 4–6 respectively are generated.

(2) First candidate list of shapes DB^{FD} from shape dataset DB is identified using indexed shape matching in FD space previously mentioned in Section 4. The number of candidate samples retrieved is given as the value of k in k-NN query as shown in Eq. (19).

(3) Identify second candidate list of shapes $DB^{\widetilde{IDSC}}$ from shape dataset DB using shape matching in $\widetilde{IDSC}$ space as presented in Section 6.

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Table 1
An overview of the datasets used for experimental purposes.

Dataset	Description	Total # of shapes	# of classes	# of shapes per class
MPEG-7	Commonly used shape dataset for evaluation of shape matching approaches. Standard metric for measuring effectiveness of shape representation and matching approaches is bulls-eye score.	1,400	70	20
Tari	Shape dataset similar to MPEG-7 dataset but has more articulation changes within each class.	1,000	50	20
Swedish Leaf	Shapes of leaves from a leaf classification project at Linkoping University and the Swedish Museum of Natural History.	1,125	15	75
Silhouette dataset	Popular database used for evaluation of shape matching techniques in the existence of articulation and other possible shape distortions.	99	9	11
Urdu ligature dataset	Database containing ligatures from Urdu language. Urdu characters are joined together to form ligatures which can be further combined to represent Urdu words. Various samples of different scale and rotational alignments for each ligature are generated.	141,190	2017	70

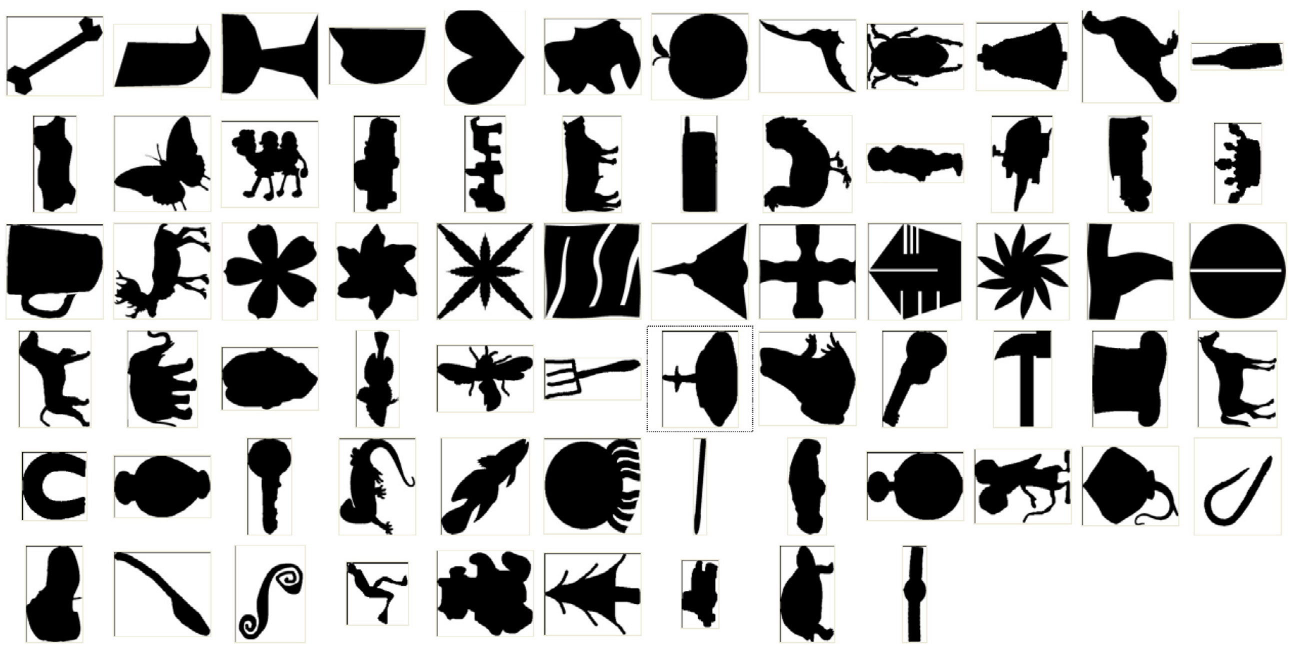

Fig. 6. Sample shapes from MPEG-7 dataset which contain one shape per class.

(4) Set:

$$DB^{pruned} = DB^{\widetilde{IDSC}} \cup DB^{FD}. \tag{25}$$

(5) Then the distance of all the shapes that are chosen in DB^{pruned} is calculated with the query shape being able to use *IDSC*-based feature space representation as identified in Section 5.

(6) Consider D^{IDSC} and D^{FD} to be a vector consisting of *IDSC*-space and *FD*-space distances of shapes from pruned dataset DB^{pruned}. Then a z-score normalization of D^{IDSC} and D^{FD} is performed and computation of the hybrid distance of k-NN shapes from query is as stated:

$$D^{hybrid} = \frac{D^{IDSC} + D^{FD}}{2}. \tag{26}$$

(7) The distance D^{hybrid} to $\overbrace{D^{hybrid}}$ is matured by using improved mutual kNN graph based analysis of shape manifold as propound in [28].

(8) The shapes are thus sorted according to $\overbrace{D_{hybrid}}$ distance which then correspond to the real k-NN to query shape representation

$$k - NN(Q, DB_{pruned}, k) = \{C \in DB_{pruned} | \forall R \in C,$$
$$S \in DB_{pruned} - C, \overbrace{D_R^{hybrid}} \le \overbrace{D_S^{hybrid}} \wedge |C| = k\} \tag{27}$$

where $\overbrace{D_R^{hybrid}}$ and $\overbrace{D_S^{hybrid}}$ are the transformed hybrid distance of shapes R and S in DB_{pruned} according to query shape Q.

8. Results obtained from experiments

In this particular section a few of the results that show potency of the proposed shape matching technique such as compared to the other state of art approaches, are presented. The comparison is done w.r.t. two effectiveness measures i.e. efficiency and accuracy when a very large dataset of shapes is under consideration.

8.1. Experimental datasets

Experiments are conducted on a number of shape datasets including MPEG-7 dataset [29], Tari dataset [3], Swedish leaf dataset [46], silhouette dataset [44] and Urdu ligature dataset. The properties that can be referred to as characteristics of these datasets are summarized in Table 1.

8.2. Experiment 1: Performance of proposed framework

This experiment was conducted to analyze the performance and efficiency of using pruning mechanism with little impact on accuracy. The experiment was done on MPEG-7 dataset.

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MPEG-7 dataset has been mostly used for evaluation of shape matching methods using center score. The dataset is selected because it offers objects varieties with real world distortion such as articulations, cracks, affine deformations and occlusion. Fig. 6 displays one image per shape class from MPEG-7 dataset. We generated FD-based shape features of shapes in MPEG-7 dataset. The selection of m is carried out using empirical evaluation. Setting values of m between 10 and 20 gives almost consistent performance with minor variations in retrieval/classification accuracies. We assumed $m = 16$ in Eq. (5) based on empirical evaluations. However, our approach is not considerably sensitive to the accurate value of m as the major contribution of shape matching is removal of dissimilar shapes w.r.t. query. FD descriptors are then indexed through the use of hierarchical tree based indexing structure to let elimination of unrelated shapes and speed up the shape matching algorithm in large datasets. *IDSC* based shape descriptors are thus generated through the description available in Section 5. In order to be consistent with [31,28,6], 100 sample points are selected on the contour for *IDSC* descriptors. $\widetilde{IDSC}$ based shape descriptors are generated as previously mentioned in Section 6. Initially *FD* based shape matching and $\widetilde{IDSC}$ based shape matching are executed to fetch 150-NN results from the shape dataset. A candidate subset of shapes is produced by combining the two subsets of shapes. The subset of the candidate has just 209 shapes through MPEG-7 dataset which is less than **15**% of the complete number of shapes available in MPEG-7 dataset. A hybrid shape matching, using *IDSC* and *FD* based shape matching, is then performed only on a subset of candidates as mentioned in Section 6. Standard pivotal score is used for comparison of the performance of the proposed hybrid approach to the state-of-the-art techniques. All shapes in the dataset are like a 40-NN query and the total number of shapes from the same class in the result set is conveyed to the user. Bulls-eye/pivotal score is the computation of the ratio of the total number of shapes obtained from the same class relative to the query and the maximum number of correct retrieval ($20 * 1400$). We have computed the bulls-eye score using four different settings to highlight the performance of different components of the proposed framework: (i) Coarse Shape Matching (ii) Fine Shape Matching without Pruning (iii) Fine Shape Matching with Pruning (iv) Hybrid Shape Matching without Pruning (v) Hybrid Shape Matching with Pruning. The efficiency of our proposed system in above five settings is computed as the time taken to execute a 40-NN query. Results to highlight the accuracy and efficiency of the proposed approach in different settings are presented in Table 2. It can be observed that the proposed coarse shape matching using indexing is remarkably fast and helps in quickly pruning disjoint shapes w.r.t. query. It is also seen that our proposed pruning approach significantly improves the efficiency whilst having little impact on accuracy. From Table 2, it can also be noted that combining coarse and fine shape matching in a hybrid framework and employing graph analysis significantly enhances the performance of sophisticated shape matching approach. The efficiency of shape matching techniques without pruning deteriorates linearly with the increase in the number of shapes in the dataset. This is not the case when pruning mechanism is employed as complex shape matching is done only with a considerable small subset of shapes as demonstrated in experiment 3.

8.3. Experiment 2: Comparison

This section provides a comparison of the proposed framework with the competitive techniques. This experiment was conducted on MPEG-7, Swedish leaf and Silhouette datasets.

Table 2
Performance analysis of proposed approach using different settings of proposed framework.

Method	% accuracy	Efficiency (Time Taken)
Coarse shape matching	71.39	0.06 s
Fine shape matching	85.54	8.3 s
Fine shape matching + pruning	85.39	1.7 s
Hybrid shape matching	94.13	9.2 s
Hybrid shape matching + pruning	94.01	2.1 s

8.3.1. MPEG-7 dataset

The experimental setup using MPEG-7 dataset is same as specified in Experiment 1. Bulls-eye score is used for comparing accuracies of retrieval of variety of approaches with our proposed framework, on MPEG-7 dataset. The statistics of comparison are shown in Table 3. Our proposed framework yields maximum bulls-eyes score among all the current state of art techniques. The pruning ability of our proposed hybrid approach is highlighted in Experiment 3.

8.3.2. Tari dataset

Tari dataset [3] is similar to MPEG-7 dataset but contain more articulation changes and is built to have large intra-class shape deformation. The experimental setup is same as specified for MPEG-7 dataset. Table 4 presents the bull-eye score of variety of approaches. Our proposed hybrid shape matching framework outputs superior performance as compared to the competitors.

8.3.3. Swedish leaf dataset

The Swedish leaf is a leave dataset. It has 15 Swedish leaf classes including the shapes of 75 leaves in each class. Fig. 7 displays one image from each leaf class of the dataset. For our proposed hybrid shape matching, we generated *FD* descriptor using top 16 lower order Fourier coefficients as specified in Eq. (5). Hierarchical tree based indexing structure is also generated to further speed up the FD-based shape matching. *IDSC* based shape descriptors are generated as described in Section 5. Similar to the experimental settings in [31], we choose 128 contour sample points for *IDSC* descriptors. $\widetilde{IDSC}$ based shape descriptors are produced as depicted in Section 6 respectively. Training data 25 leaves are randomly selected from each class and for testing remaining 50 leaves per class are used. 50 times the experiment was repeated. In each iteration different training shapes are randomly selected and to get rid of any prejudice associated with favorable shape selections of the 1-NN classification accuracies are averaged. Table 5 presents 1-NN classification accuracies of various shape matching techniques computed on Swedish leaf dataset. The results yield that our proposed framework outperforms the competitor shape matching techniques.

8.3.4. Silhouette dataset

High noise level is considered in this experiment setup. For base case establishment, two different schemes for comparison are implemented, critical invariants and differential invariants. We selected a subset of 24 specific shapes from silhouette dataset to make the experiment consistent with the one reported using integral invariant and differential invariant as reported in [35]. The silhouette dataset provides manually labeled shapes and so in this experiment effects of noise are simulated. Noise is incorporated by translating all contour points by a measurable distance d which determines quantity of the induced noise. Suppose if $\mathbf{S}$ represents the original data, a noisy dataset $\mathbf{S_C}$ is generated by addition of the term $N[0, \sigma]$ to each (x, y) coordinate on the contour in the normal direction. We set $\sigma = 3.0$ to simulate high level of noise in shapes. Each noisy trajectory in $\mathbf{S_C}$ is thus selected to be set as an example

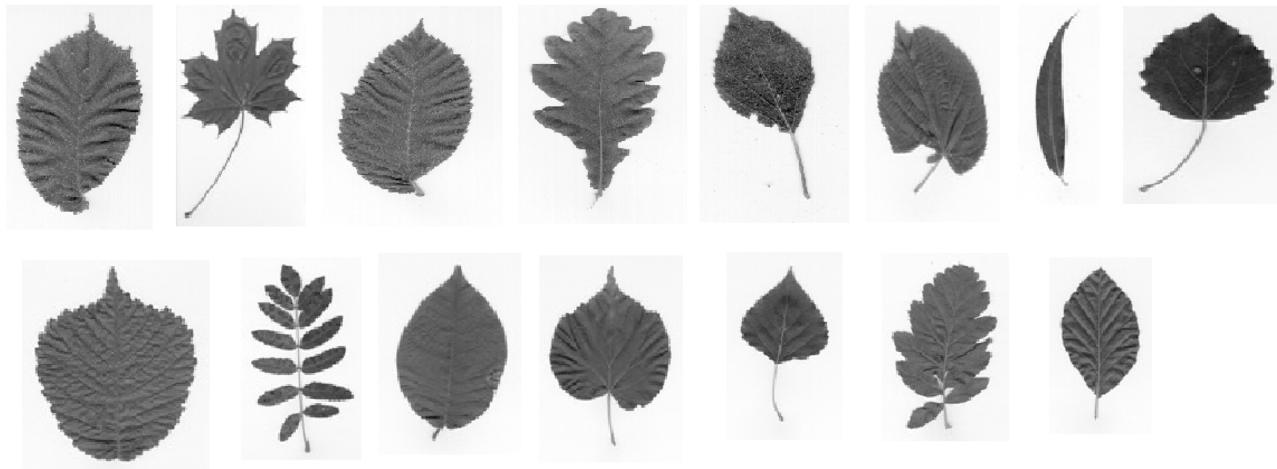

Fig. 7. Sample shapes from Swedish leaf dataset which contain one shape per class.

Table 3
Comparison of proposed hybrid shape matching approach with its competitors who also use MPEG-7 dataset.

Method	SC [9]	Aligning Curves [43]	Skeletal Context [54]	Optimized CSS [37]	Contour Seg. [5]	*IDSC* [31]
Score (%)	76.51	78.16	79.92	81.12	84.33	85.54
Method	Symbolic Rep. [16]	Hier. Procrustes [36]	Triangle Area [2]	*IDSC*+ Graph Transduction [6]	*IDSC*+ Graph Analysis [28]	Proposed Hybrid Approach (with pruning)
Score (%)	85.92	86.35	87.23	91.61	93.40	94.01

Table 4
Comparison of proposed hybrid shape matching approach with its competitors who also use Tari dataset.

Method	SC [9]	*IDSC* [31]	SC + Graph Transduction [6]	*IDSC* + Graph Transduction [6]	*IDSC* + Graph Analysis [28]	Proposed Hybrid Approach (with pruning)
Score(%)	94.17	95.33	97.79	99.35	99.41	99.99

Table 5
Comparison of 1-NN classification results of proposed hybrid shape matching approach with competitors who use Swedish leaf dataset.

Method	% accuracy
Fourier descriptors [31]	89.60
SC + DP [31]	88.12
IDSC [31]	94.13
IDSC + Graph Transduction [6]	95.71
IDSC + Graph analysis [28]	96.83
Proposed hybrid method	97.17

Table 6
Average response time to execute 100-NN query for varying number of samples using *IDSC* and proposed hybrid approach.

# samples	*IDSC* [31]	Proposed hybrid approach
6,000	34.25 s	2.13 s
9,000	51.42 s	2.37 s
12,000	68.76 s	2.55 s
15,000	86.17 s	2.71 s
18,000	103.13 s	2.83 s

query Q_C and search is done on set k nearest matches in the original dataset **S**.

For the proposed approach, pruning distant shape steps are ignored. Hybrid shape matching, employing *IDSC* and FD based shape matching, is thus applied over the whole dataset relative to the stated query shape. The process of adaptation of local-area integral invariants [35] is used for implementing the integral-invariants. Differential invariants implementation is based on the adaptation of curvature invariants [13,12]. Retrieval of noise causing shapes from a given subset of silhouette dataset are shown in Fig. 8. Graphical representation of shape distances is shown for effective visualization. Lower gray levels show low distances and vice versa. Best match is the minimum distance for the noisy query sample is shown by diagonal entries. A block diagonal structure with low gray levels parallel to the diagonal is preferred. The proposed shape matching approach gives superior performance by having lower distances along the diagonal resulting into a good block diagonal structure, along with integral-invariant based approach. Differential invariant does not present a block diagonal structure due to the presence of high distances along the diagonals. The results presented in Fig. 8 demonstrate the robustness of proposed shape matching approach to the existence of noise in shapes in comparison with the competitors.

8.4. Experiment 3: Efficiency experiments

This experiment is conducted to highlight the performance efficiency of the pruning capability of our proposed hybrid shape matching framework. MPEG-7 dataset is considered and bulls-eye metric is used once again for calculating the retrieval efficiency. Count of selected shapes in the pruned datasets as described in Eq. (25) is used for performing shape matching using complex and computationally heavy *IDSC* based shape matching. The bulls-eye score for various percentages of given samples in the candidate subset of shapes shown in Fig. 9. As it is obvious from the figure, the proposed hybrid approach surpasses performance of competitors by just using shape matching on 10% of the shape dataset. The percentage of sample required for effective shape matching will decrease with the increase in the size of shape dataset, as demonstrated in the next experiment.

To further validate the scalability of proposed shape matching framework in the existence of stated large shape datasets, we

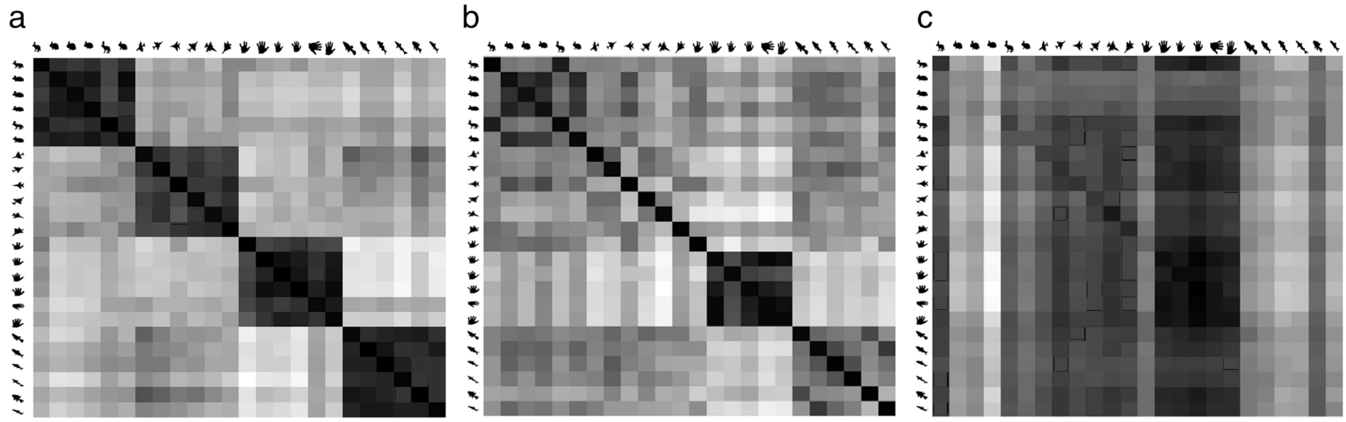

Fig. 8. Shape distances calculated using (a) proposed hybrid approach (b) integral invariant (c) differential invariant. Lighter shades are used to represent high distances and vice versa.

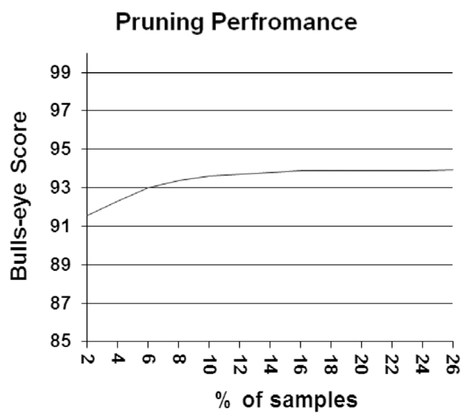

Fig. 9. Bulls-eye score achieved using different % of samples for sophisticated shape matching.

combined projectile points dataset[1] containing 16,000 samples with MPEG-7, Tari, Swedish leaf and KIMIA 99 datasets resulting in 19,000+ samples. To establish the base case, we implemented *IDSC* [31] based shape matching techniques which we are employing as our fine shape matching approach. This allows us to have a relative comparison with our nearest competitors w.r.t. accuracy such as *IDSC* + Graph Transduction [6] and *IDSC* + Graph Analysis [28] that apply post processing step on *IDSC*-based shape matching [31]. These techniques will require more time to yield a *k*-NN query as compared to *IDSC*. We implemented all these mentioned algorithms with the help of MATLAB 11 and execution times were noted on Intel Core i5 3.20 GHz with 2GB RAM. We obtained each sample from the dataset in a sequential manner and executed a 100-NN query on the remaining dataset. Average query time noted for obtaining 100-NN results with the use of various shape matching approaches are presented in Table 6. It can be seen from Table 6 that the proposed hybrid shape matching framework performs well compared to the competitors relative to the scalability in the existence of the large shape datasets. The proposed shape matching approach consumes significantly lesser time as compared to its competitor although it is a hybrid shape matching mechanism. The significant reduction in computational complexity is attributed to our proposed pruning approach based on hierarchical tree-based indexing and retrieval in our coarse shape matching module as presented in Section 4. A very small subset of candidate shapes from dataset is identified by performing extremely efficient coarse shape matching. The performance is significantly enhanced further by employing tree based indexing approach. Hybrid shape matching employing accurate but computationally complex shape matching approach is only employed on a very small subset of shapes. The pruning performance as highlighted in Fig. 9 shows that the proposed approach achieves higher accuracy by performing computational expensive fine shape matching on a very small subset of dataset. The pruning power enhances with the increase in the database set thus resulting in almost consistent retrieval time for large to very large datasets. This scalability of our proposed approach to large dataset is evaluated in Experiment 5.

8.5. Experiment 4: Scalability to large databases

The aim of this particular experiment is to demonstrate its scalability in the stated shape matching framework to very large databases. Fig. 10 shows one picture per ligature class extracted from the Urdu ligature dataset. The experiment is conducted on Urdu ligature dataset containing 141,190 samples. For our proposed hybrid shape matching, we generated *FD* descriptor using top 16 lower order Fourier coefficients as specified in Eq. (5). Hierarchical tree based indexing structure is generated to further speed up the FD-based shape matching. The generation of *IDSC* descriptors is briefly described in Section 5. We selected 100 points as a sample on the contour to be further used for *IDSC* descriptors. $\widetilde{IDSC}$ based shape descriptors are thus generated as previously mentioned in Section 6 respectively. We performed leave one out cross-validation and 100-NN query using our proposed shape matching framework. To highlight the pruning power of our approach using proposed hierarchical indexing structure, we present the fraction of samples that have to be retrieved from disk to perform complex shape matching whilst giving same performance as sequential shape matching. The proportion of samples retrieved for execution of 100-NN query in the presence of various number of shapes in database are presented in Fig. 11. It is obvious that the percentage of samples obtained to be able to answer a query decreases with the increase in size of database thus resulting in nearly consistent query execution time for varying size shape database. Hence, our proposed shape matching framework enables time-consuming complex shape matching techniques that are applicable in the existence of considerably large number of samples in datasets.

[1] Available at: http://www.cs.ucr.edu/eamonn/shape/shape.htm.

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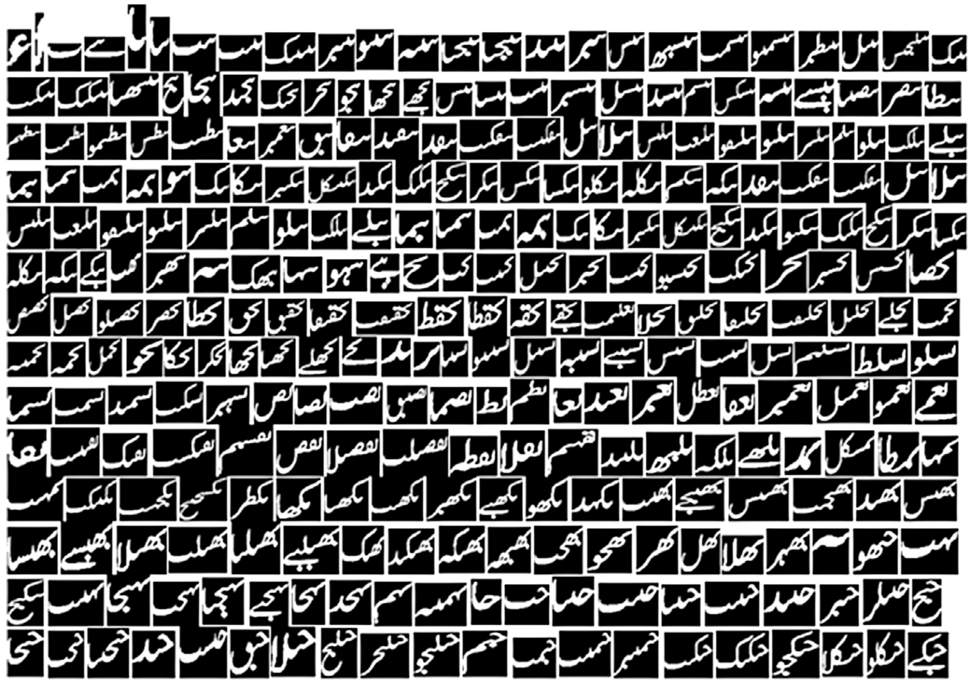

Fig. 10. Sample shapes from Urdu ligature dataset consisting of one shape per ligature class.

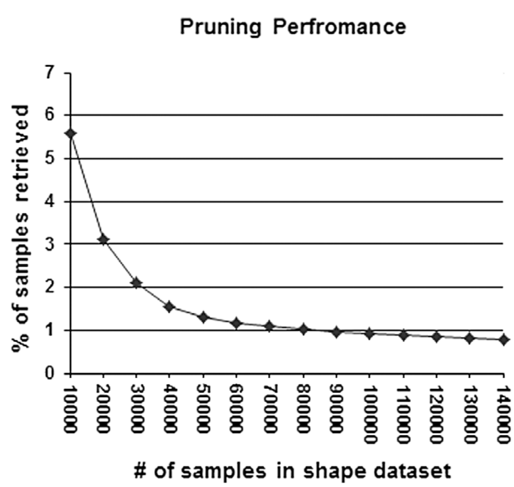

Fig. 11. Average percentage of samples retrieved to answer 100-NN query by using different number of samples from Urdu ligature dataset.

9. Discussion and conclusions

We discussed shape matching in detail in the presence of articulation, affine deformation, noise and other distortions such as occlusion, in this paper. A shape matching framework is proposed that generates many contour based feature of shapes for shape matching. Compressed Fourier descriptors based shape representation is generated and incorporated in the framework for two major merits: (1) Hierarchical tree based indexing structure results in fairly fast shape matching that can be made use of accurately for a coarse shape matching and pruning of dissimilar shapes and (2) Also it can form a combination with complex shape features like *IDSC* to build up their shape matching accuracies. *IDSC* descriptors are capable to accurately model complex shapes suffering from the problems of occlusion, articulation and other affine distortions. We have also presented an $\widetilde{IDSC}$ based shape descriptor which is an approximation of *IDSC* descriptor for coarse but efficient shape matching. $\widetilde{IDSC}$ models the shape using different perspective as compared to FD descriptor and helps in generating an accurate set of candidate list while trying to minimize false negatives. The major achievement of this paper is a hybrid shape matching framework which enhances retrieval and classification accuracies of existing state-of-the-art techniques while significantly reducing their computational complexity. The proposed framework can be incorporated with any of High-ranked shape matching algorithm in order to increase its shape matching efficiency and also significantly aiming to reduce the computational cost which makes it scalable to gigantic datasets. In our future work, The analysis of the proposed approach will be carried out in cluster/cloud platforms.

Multiple experiments were conducted to able to view the effectiveness of proposed hybrid shape matching framework using different shape datasets. Experiment performed on silhouette dataset shows that our proposed method gives better retrieval accuracies than the remaining competitive techniques like differential invariants and integral invariants under perturbation while being in the coexistence of high noise level. Results have shown that MPEG-7 and Swedish Leaf datasets give best possible retrieval and classification accuracies using proposed hybrid approach however the proposed approach applies complex shape matching on a very considerably small subset of shapes. We, thus have managed to achieve a bulls-eye score of 94.01% on MPEG-7 datasets which is so far best scores on well-known MPEG-7 dataset. Moreover, this accuracy is obtained by applying sophisticated shape matching on perhaps only 15% of the shapes in MPEG-7 dataset that depicts the application of proposed approach to gigantic shape datasets.

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