Shape Based Image Retrieval: A Review

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Abstract— **Content Based Image Retrieval (CBIR) system is an approach to search images and retrieve relevant images from image databases using visual content (information) of an image. In today's scenario, CBIR receives a query object as input and retrieves similar objects as output from an image database according to a similarity/distance measure. Generally, color, texture, shapes or any combinations of them could be used as visual contents (feature) for image retrieval. Among them, shape is one of the most important features used in CBIR. While performing Shape based retrieval, it involves three primary issues in retrieving images namely Shape Representation, Shape Matching (Similarity Measures) and Shape Indexing. Also, it is important that the descriptors need to extract the characteristics of objects being robust to image rotation, scale changes, illumination variation, occlusion, noises and change of views etc. Motivated by the above factors, this paper gives a short review involving Geometrical and Structural Shape Representation of descriptors and a few Shape Matching algorithms.**

Keywords-shape descriptors; similarity measures; geometric matching; structural matching

I. INTRODUCTION

In Image Processing, the key factors used to match the images are based on Colors, Textures and Shapes or any combinations of them. Among them, shape is the most widely used image characteristic, exploited for describing image content [5]. Shapes could act as a significant feature for matching/retrieving similar images. Image matching based on shapes is a challenging task and it can be performed in following phases: Initially, interesting keypoints are detected from the images. Then, descriptors are extracted to characterize the local keypoints of the image. As a final step, matching of key points is accomplished according to the similarities of the descriptors of interesting points obtained from different images [16].

Keypoints are detected using various detection methods like Canny edge detector, Sobel edge detector, Harris corner, Laplacian Of Gaussian blob detector, Harris Laplace affine detectors, Hessian Laplace affine detectors etc. Once keypoints are identified, they are characterized by using shape descriptors. A shape descriptor is a set of values that attempts to quantify the shape features in ways that agree with human intuition. Using keypoints, the shape descriptor should be able to represent original shape as well as distinguish two shapes [16].A good descriptor must fulfill the following requirements: (i) it must be unique for each shape; (ii) it must be robust to scale, rotation and little distortions; (iii) it must not depend on the initial points; and (iv) it need to be fast and easier to obtain [18]. Some of the descriptors are SIFT and it's variant (PCA-SIFT), GLOH, shape context, Surf, HOG and the autocorrelation of local gradients, etc.

Generally shape representation and description techniques [3] are classified as contour based and region based methods. In contour based methods, the shape features are extracted from the shape boundary information whereas in region based methods the shape regions are used to extract features. Both these methods are further divided into global (continuous) and structural (discrete) methods. Global methods have feature vectors for the entire shape without any further splitting of the shape and Structural methods divide the boundary/region of the shapes into number of primitives based on particular criteria. Some of the descriptors used under these four categories are listed as:1)For global contour methods, circularity, eccentricity, major axis orientation, shape signature, Fourier and wavelet descriptors, autoregressive descriptors are used;2) For Structural contour methods, descriptors used are Chain code, B-spline, shape invariants;3) For global region methods, area, Zernike moments, generic Fourier descriptor, shape matrix, Euler number are used as descriptors;4)For structural region methods, convex hall, media axis descriptors are used.

Therefore, Shape descriptors for different images are compared for image matching using shape similarity methods. Shape similarity [1] is defined as a mechanism which tries to find whether the two images are similar/dissimilar using global or local schemes. Global methods consider the shape as a whole, representing it by a single global descriptor, such as the shape's area, aspect ratio, Fourier-based descriptors and invariant moments etc. Shape similarity is then determined by the difference of those global descriptors. In contrast, Local Methods represent a shape by a set of Local Shape Descriptors (LSDs), each corresponding to a certain part of the shape along its contour. In order to compute the similarity measure, the corresponding local features across the different shapes are matched, and these local similarities are integrated into a global score. A common practice is to optimize an objective function that comprises of local similarities, with respect to the assignment function, and use its optimized value as similarity score.

Here, every work has been reviewed in the perspective of shape representation using shape descriptors and similarity measures (matching algorithms) for the domain of Geometrical and Structural shape mechanisms.

II. REVIEW OF SHAPE MATCHING TECHNIQUES

A. Geometry Based Shape Matching

Geometry based Shape matching is a mathematical approach of matching the geometrical properties like points, lines, curve, circle etc. This geometric features are usually enough to represent any given shape of an image. So with the help of the geometric features, shape matching is performed to improve the accuracy.

i. Point based matching

Here, image matching is performed based on a single point or tuples of point matching. In a set of single point matching, it considers a point from the source image to match a point in the target images and these points could be an edge or a corner. Image matching done in this way may sometimes fail, if the images hold similar local appearances. So to improve the matching accuracy, a better solution is to include some additional constraints like distances, angles between the points, which has lead to the development of tuples of point matching techniques. Tuples of point matching may refer to point pair matching, triple point matching or higher point matching. In point pair matching, two points separated by a fixed distance and in triple point matching, a triangle of three points, having same total angle value or same distance value is used to compute image matching. Thus the accuracy is increased with the additional burden of computational cost. Some of the point based matching methods are reviewed here.

Jianning Liang et al [9] proposed an image matching method based on the gradient space. Initially, scale-invariant keypoints have been detected by combining image pyramid and response strength of the Hessian matrix. A new local descriptor robust to rotation has been constructed by finding gradient space along the horizontal and vertical directions and a principal direction has been used as the orientation of the key points. Then orientation–magnitude histogram has been constructed based on the polar coordinate and a L1 norm distance has been used for image matching. Steepest descent strategy has been applied to further remove the mismatches that may occur. Images with different transformations are applied and the results for these transformations are listed.

Glauco V. Pedrosa et al [5] have proposed a matching algorithm by defining a new shape descriptor called Shape Salience Descriptor (SSD) using salience points. The methodology used three steps: the salience points have been selected , represented using their relative angular position of the shape's centroid and a similarity measure have been calculated with different number of salience points and finally optimized using Dynamic Programming(DP) algorithms. Apart from this, global features of the shapes have been incorporated in the similarity distance, referred as Shape Salience Descriptor with Global Features (SSD+GF).Thus this method has achieved retrieval precision performance as 85%,98% and 96% for the datasets MPEG-7 CE-shape-1 part B,Kimia-99, Kimia-216 respectively.

Jinglun Shi et al [11] have proposed a point based matching method by investigating artificial bees. Each artificial bee, starting at a random point in the source image, has been used to find the corresponding matches in the target images iteratively. Then this information have been exchanged and evaluated to find an optimal matching using proximity-regularized cost function and thus image matching has been performed. Silhouette images of fish and hand test datasets are used to yield more accurate matching results.

Zhi-Quan Cheng et al [19] have presented an algorithm for finding correspondences between the features, independent of feature description. SuperMatching has been formulated using Supersymmetric tensor by considering feature similarity and geometric constraints between features. For matching, the affinity between two point triples, the similarity of the angles of the triangles formed by the triples has been measured that does not change with reordering of elements. A new supersymmetric affinity tensor definition has been introduced to devise a compact higher order power iteration solution for the higher order matching problem. Various data like surface color information data, articulated shape synthetic data, isometric deformable surface data are experimented to show the high accuracy rate in the retrieval images.

ii. Line, Curve, polygon based matching

Line, curve, polygon are the categories of geometrical properties. Lines calculated from the images can be used as a feature for image matching. Curve includes circle, ellipse, semi-circle etc which are helpful for extracting needed features for matching. Similarly different polygon shapes (like triangle) are also considered for image matching. Each method has its own strength and based on the requirement, a particular method can be chosen.

Min Chen et al [13] have proposed a line based matching method which is invariant to scale and rotation. Initially, lines have been created from the extracted boundary points and saliency-lines and a control network have been constructed for every image. For each saliency-line, a corresponding saliency-line has been found out in the target image. Then, general-lines have been clustered and a sub control network has been created from the remaining lines. Finally, image matching has been performed between the two subcontrol networks for which the root nodes have correspondences. The areas of city and farmland of GeoEye-1 images are the datasets used to achieve recall performance as 95.94 % and 96.14 % respectively.

Huijing Fu et al [8] proposed a new affine-invariant curve matching algorithm for occluded object recognition. First, an affine-invariant signature has been defined, inspired by the expression of affine curvature. Subsequently, a novel Affine-Invariant Curve Descriptor (AICD) sampled at affine length has been constructed to characterize the local shape of a curve based on the signature. Finally in this research, an affine-invariant part-to-part curve matching algorithm has been proposed by combining AICD with a curve segmentation strategy based on inflexion points (curvature zero crossing points). Fish shape, MCD and MPEG-7 databases are used to evaluate and found the retrieval accuracy as 91.17%, 97.02% and 84.6% respectively.

Wonil Chang et al [16] have proposed an object detection algorithm based on an object's sketch. Initially, circular arcs have been segmented. Many new descriptors have been computed namely end point, unary arc and binary arc descriptors based on their end points and their directions. Then an object model has been created using Attributed Relational Graph (ARG) using circular arcs as nodes, neighbor relations between circular arcs as edges, unary arc descriptors as node attributes and binary arc descriptors as edge attributes. For object detection, shape patterns in the test images have been compared using unary arc descriptors and binary arc descriptors which are invariant to scale changes and rotation. ETHZ datasets are used and achieved the performance for apple logos, mugs as 97.7% and 95.5% respectively.

Jianfang Dou et al [10] used Delaunay triangulation method for image matching. Initially Hessian affine keypoints with SIFT descriptors have been matched using Euclidean distance to get initial keypoints and using this keypoints, Delaunay triangulation have been constructed. Based on the structure of Delaunay triangulation, keypoints have been divided into two classes, one class with the same number of neighbor triangles, the other class with different number of neighbor triangles. For image matching, matched triangles have been found out from these two classes and local affine invariant geometric constraint have been adopted to get the final matched keypoints. ZuBuD database are used for image pair 1, 2, 3 to achieve accuracy as 72%, 46% and 44% respectively.

iii. Blob and Graph based matching

A blob is a region of a digital image in which some properties are constant or vary within a prescribed range of values. All the points in a blob can be considered in some sense to be similar to each other. Blob detection is used to obtain regions of interest for further processing which may not be possible with other edge or corner detectors. These regions could signal the presence of objects or parts of objects in the image domain which finds application in object recognition and/or object tracking.

Graphs are a flexible and powerful representation mechanism for complex scenes that have been successfully applied in computer vision, pattern recognition and related areas. When graphs are used to represent objects of a particular domain, the recognition problem turns into the task of graph matching. It can be formulated as an attributed graph matching problem, where the nodes of the graphs correspond to local features of the image and edges correspond to relational aspects between features. Graph matching then used to match the correspondence between nodes of the two graphs such that they look most similar. Some of the research works done in this area are reviewed below.

Chunhui Cui et al [2] have proposed an approach to remove the false matches and to propagate the correct affine invariant features. Initially, pair-wise Affine Consistency (AC) measure has been computed using local affine information to remove the unreliable matches. This measure works well for high textured regions but it terribly fails to recognize and segment the objects properly for low textured regions. So a global match refinement and propagation approach have been proposed where in global match refinement, along with the existing intensity and color similarity, smoothness term has been included to find the optimal set of affine transform. In the propagation approach, more feature correspondences have been generated from the initial seed matches and thus the most unreliable matches have been removed. Leaf recognition and different low textured images are compared against their local representations and was able to achieve an overall recognition rate as 85%.

Amir Egozi et al [1] have proposed two matching approaches for improving the retrieval of shapes. Initially Local Shape Descriptor (LSB) has been calculated on both the images. For matching the two shapes, similarity measures have been computed using assignment matrix and pairwise affinity matrix and optimized using spectral relaxation. Secondly, a graph based approach called shape meta-similarity approach has been introduced which agglomerates pairwise shape similarity to reject outliers and thereby improved the retrieval accuracy. MPEG7 CE-shape-1 database achieved the overall retrieval rate as 92.5%, Articulated Data Set and Kimia Silhouettes Database are used to achieve the retrieval rate greater than 95%.

Wei Lian et al [15] have proposed two methods of shape representation for rotation-invariant nonrigid point set matching using Shape Context (SC). Here, the point sets have been converted to a graph using two approaches: Minimum Spanning Tree induced Triangulation (MSTT) and Star Graph (SG). For MSTT method, the frame edges and the boundary edges have been created and oriented SC has been computed using these two edges and finally optimized using Dynamic Programming (DP) algorithm. As the time complexity of this method is high, it has been simplified to a star graph where the shape representation is same as that of MSTT method except that no boundary edges were used. Thus by matching edges between two point sets, SC rotation invariant has been achieved. Various objects of ETHZ data sets are compared against many techniques to show the improvement in accuracy of image matching.

Gerard Sanromà et al [4] have proposed a graph based matching technique. Initially using correlation or feature descriptors matching features have been found and refined further to contain dense correspondence set using graph matching technique. Graph matching, one of probability mixture modeling has been aimed to recover the set of correspondence indicator S using structural and geometrical information which is used as a density function. Then Expectation Maximization (EM) algorithm has been applied to find the Maximum Likelihood (ML) estimate of the correspondence indicators and used Softassign algorithm to solve the assignment problem that allowed to smoothly detect outliers. GREC database, Shape database are the datasets used and improved the image comparison performances which ranges from 85% to 100% for different object.

Jun Tang et al [12] have proposed a point pattern matching method using spectral graph analysis. Initially, spectral context have been constructed and obtained Eigen values which has been used as point features. Then a geometric consistency strategy has been derived from the order relationship, which resisted positional jitter, outliers and some transformation invariance. For matching using spectral context and geometric consistency, a function f which is representated as a matrix P has been applied and an optimization of P has been performed using probabilistic relaxation. Thus the local spectral descriptor benefited from the proposed geometric consistency and used various types of data like Synthetic data, CMU/VASC house sequence, and ALOI image library to show improvements in their performances.

Hongliang Li et al [6] have proposed an object detection method based on co-saliency by computing the IntrA-Image Saliency (IaIS) and InteR-Image Saliency (IrIS) maps. In IaIS, a new saliency detection method has been proposed based on the multiscale segmentation voting and segmented to extract foreground image from the background and further the objects have been extracted at various scales. In IrIS, the RGB color histogram based on a pyramid structure has been computed. For local image matching, three local appearance descriptors have been used and a Minimum Spanning Tree (MST) has been constructed based on the ranked similarities. To measure the pairwise similarity, the correspondence matrix between regions have been computed by optimizing it using linear programming algorithms and the total matching similarities for all the groups have been calculated. Compared with the RC saliency model, IaIS achieved about 10.9%, 0.71% and 11.83% improvements of Recall, Precision and F-measure respectively on the ICoseg dataset.

Xiang Bai et al [17] have proposed a method to improve the similarity measure further from the existing similarity measures. A new distance function has been learnt in an unsupervised setting using graph transduction where the knowledge of intrinsic shape differences has been included. Using this similarity measure, the shapes have been arranged correctly based on their ranks and thereby it is able to include the more relevant image information and rejects all other less relevant information. MPEG-7 datasets are used to achieve the retrieval accuracy as 91.61%

B. Structural based Shape Matching

The Structural shape matching includes features that are based on structures which may be parts of an object or symmetric resemblance of an object with various transformations. It provides a higher level of compositional shape description which could discriminate a level higher than the geometrical shape description by updating its similarity measure. Normally, human recognizes a shape not only by its local and global geometrical variations, but also by a high-level understanding of the shape structure. So to improve the retrieval accuracy of semantically related images, a combination of structural and geometrical features have been adopted.

Huigang Zhang et al [7] have proposed a structural based method to detect objects. The feature descriptors have been extracted from Pairs of Adjacent Segments (PAS) features and its context information. Using EMD (Earth Mover's Distance), the foreground features have been selected automatically. Then a part-based shape model has been constructed by clustering the parts of the image using location descriptors; using PAS context descriptor to have clusters with semantic meanings and filter each semantic cluster to give more accurate part models. Finally the object detection has been performed by matching each testing image with the newly constructed model using Euclidean distance. The data sets used are ETHZ Shape Dataset, INRIA Horse Dataset and PASCAL 2007 Dataset and they are evaluated to achieve the performance more than 90%.

Seungkyu Lee et al [14] proposed a new matching framework by unifying structural shape features with the geometrical shapes. The rotation and reflection symmetries of structural shapes have been calculated. To obtain matching, initially, symmetry likelihood has been computed by multiplying their symmetry strengths. Also, similarity between two geometrical shape descriptors has been obtained. Finally a new symmetry driven similarity using Bayesian framework has been constructed using the likelihood similarity of the symmetrical shape as a weight on the geometrical similarity. The retrieval accuracy for combination of IDSC, mutual graph and symmetrical method using MPEG-7 shape dataset has achieved the performance accuracy as 96.42%.

Yu Shi et al [18] have proposed a global space symmetry matching technique. Initially a central axis has been detected by comparing the distance between any two of the corners which includes common and remote corners. From this, a new global shape descriptor has been created using the maximum distance as the diameter and the midpoint as the centre of the circumscribed circle. The Image matching has been done by finding the similarities between space symmetry length (SSL) sequences and optimized using Hidden Markov Model (HMM). The MPEG-7 shape CE Part B data set is used to get retrieval performance as 88.01%.

From the above literature an indicative table representing the segmentation methods used, the features selected by the authors, the list of transformations/ deformations applied by their algorithms on the image, comments over the work have been tabulated as shown in Table 1.

III. CONCLUSION

Image matching based on shapes is still a current research area where the shape of an object is used as a basic visual feature for describing image content. In this review, various shape representation and shape matching methods based on different geometrical methods using points, pair of points, triple points, curve, triangle, graph based and structural methods with their pros/cons have been studied. From this study, some of the improvements have been noted such as need of getting high semantically related accuracy, to eliminate the importance given more to accuracy than efficiency, elimination of high computational costs and run time since they combine many methods together to achieve better results. From our point of view, focus for further improvement may lead to the concentration on the creation of a better/strong descriptors which is instrumental for image matching, object recognition, image retrieval etc, This can be done by including structural properties of an image, including measures that may improve the efficiency and decrease the computational cost by preserving the same accuracy. Thus this paper gives a brief view on shape based image retrieval which may further help us to take research work in this path.

TABLE 1 COMPARATIVE STUDY OF EXISTING TECHNIQUES.

RNo.	Segmentation methods used	Features used	Techniques used	Transformations applied	Data sets and performance achieved	Comments
1	Any contour segmentation method to extracts points	Any Local shape descriptors(LSD) (here SC,IDSC are used), pairwise affinity matrix	Pairwise Spectral Matching and Meta Similarity Matching	Invariant to rigid, non rigid deformation, articulation	MPEG7 CE-shape-1 dataset achieved an overall retrieval rate as 92.5%, Articulated and Kimia Silhouette dataset achieved retrieval rate greater than 95%.	**Pros:** **i)** Improves the shapes retrieval rate and outperforms other schemes based on the *same* LSDs. ii) Accuracy is relatively high as similarity measures are refined using meta similarity matching. **Cons**: Run time is high.
2	Affine Harris and Affine Hessian detectors	Affine invariant features	Global refinement and propagation method for low textured regions	Robust to viewpoint change, Affine invariant,non-rigid deformation, partial occlusion, clutters and low texture surfaces	Leaf recognition image data, various image pair data and achieved an overall recognition rate as 85%.	**Pros:** i) Gives superior results when the low textured surfaces are used. ii) Global methods are used to retrieve the images at faster rate than the retrieval process done by local methods.
4	Harris corners	Delaunay triangulation features.	Graph based matching using EM algorithm	Robust to clutter, outliers, affine invariant	GREC database, Shapes database improved the retrieval accuracy more than 85%.	**Pros:** Gives better image retrieval result since structural approach is fused with geometrical approach. **Cons:** Computational time is high.
5	Any edge detection	Shape Salience Descriptor (SSD)	shape salience descriptor (SSD) using salience points	Invariant to translation, scaling, rotation, mirroring, robust to noise and shape occlusion.	MPEG-7 CE-shape-1 part B, Kimia-99, Kimia-216 data sets obtained the precision performance as 85%, 98% and 96% respectively.	**Pros:** Capable to find more semantically related images.
6	Grab-Cut segmentation	Image pyramid representation, Visual descriptors which include color, color co-occurrence and shape word.	Fusion of IaIS and IrIS methods.	-	ICoseg Database, MSRC data set achieved the Recall and F-measure as 74.22% and 31.69% respectively.	**Pros:** It helps to simulate the human's attention search process. **Cons:** **i)** Co-saliency detection may lead to false detection. ii) Identifying salient objects from complex scenes is a challenging task.
7	No explicit segmentation	Pairs of Adjacent Segments (PAS) +	Part based shape model	Robust to within-class variations and scale	ETHZ Shape Dataset, INRIA Horse Dataset	**Pros:** i) It requires much less training

		context information		changes.	improved the performance greater than 90% for different classes.	information. ii) The object model is learnt automatically without the need for bounding box of the objects. **Future work:** Need to develop a framework for the shape part description and model background distribution for better detection.
8	Canny edge detector	Affine invariant signature, affine length, affine invariant curve descriptor	ACID descriptor with curve matching algorithm	Robust to affine transform	Fish shape, MCD and MPEG-7 datasets obtained the retrieval accuracy as 91.17%, 97.02% and 84.6% respectively.	**Pros:** This approach is able to recognize objects better even with partial occlusions and affine deformation images. **Future work:** Need to improve this method by adopting a global shape similarity measure.
9	Image pyramid + Hessian matrix	Scale, rotation invariant key points.	Image matching based on orientation–magnitude histograms	Invariant to rotation, scale, translation, robust to the variation of focal lengths, illumination change, occlusion, noises and image blur.	-	**Pros:** Gives better results for the multi-view, affine transformation images and image registration.
10	Modified version of Hessian affine region detector	Delaunay triangulation keypoints	Delaunay triangulation method	Robust to occlusion, background clutter, illumination and 3D viewpoint changes	ZuBuD database for image pair 1, 2, 3 achieved accuracy of 72%, 46% and 44% respectively.	**Pros:** This approach achieves high accuracy than RANSAC based method.
11	Any segmentation method	Set of contour points	Bees Colony Optimization	Invariant to translation, rotation and scaling	Fish and hand of silhouette image Test datasets are used.	**Pros:** Use of proximity points on the contours reduces the matching process. **Cons:** High computational cost.
12	Harris corner detector	Eigen values as feature point for spectral graph and order relationship for geometric consistency.	Spectral context and geometric consistency.	Invariant to translation, rotation, scaling, jitter, outlier.	Synthetic data, CMU/VASC house sequence, ALOI image library data set are used.	**Pros:** Gives better retrieval performance for the images containing greater noise. **Future work:** i) Need to investigate the combination of Eigen - values and eigenvectors to construct structural descriptors. ii) Need to handle the problem of large deformation.
13	Canny edge detectors, Lines are generated using a new algorithm.	Saliency line , general line , single control network and several sub control network	line based matching	Robust to scale and rotation.	city and farmland areas of GeoEye-1 datasets obtained the recall performance as 95.94 % and 96.14 % respectively.	**Pros:** Only selected lines are used for image matching. **Cons:** This technique is applicable for the scaling and rotation based images alone.
14	Canny edge detector	Rotation and reflection symmetries for structural + any geometrical features	Structural matching by unifying structural shape features and the geometrical shapes.	Invariant to rotation, scaling and reflection.	MPEG-7 shape set obtained retrieval accuracy (for IDSC + Mutual Graph + Proposed) of 96.42%.	**Pros:** Any new structural features can be incorporated.
15	Any contour detector	Rotation oriented shape context features.	Graph based Rotation Invariant point set matching.	Robust to Rotation, clutters, nonrigid deformation to some extent	ETHZ data sets	**Pros:** i) MSTT can better represent point sets. ii) MSTT method outperforms in terms of robustness against clutter images. iii) SG method improves average running time. **Cons:** Time complexity of MSTT method is high.
16	Edge pixels are extracted using Maire's gPb edge detector, Circular arcs are segmented using Rosin's split-and-merge algorithm.	Circular arc segments.	Attributed Relational Graph (ARG) matching with sketches.	Invariant to scaling and rotation.	ETHZ dataset achieved the performance for apple logos and mugs images as 97.7%, 95.5% respectively.	**Pros:** Achieves better retrieval accuracy. **Cons:** It always requires image sketches. **Future work:** To learn object models from training images.
17	Any segmentation	Set of contour	Graph Transduction	Invariant to translation, rotation,	MPEG-7, Kimia's 99, Kimia's 216 data set	**Pros:** i) It improves the performance of

	method	points(IDSC)	learning algorithm	scaling and occlusion	achieved retrieval accuracy of 91.61%, 97%, 93.8% respectively.	shape classification and clustering. ii) It can be applied on the top of any existing shape matching algorithm. **Cons:** if the shapes contain many outlier, this method does not improve the result **Future work:** to improve the result even in the presence of more outliers in the shapes.
18	Canny operator and morphology methods to remove discontinuities.	Space symmetry length sequence based on circumscribed circle.	Global space symmetry matching.	Robust to scale, rotation and translation.	MPEG-7 shape CE Part B dataset achieved the performance rate of 88.01%.	**Pros:** Gives better retrieval for semantically related images. **Cons**: SSL can be applied only for closed contours images. **Future work:** Need to focus on building more stable descriptors.
19	Supersymmetric tensor with a new algorithm to extract triple point set tuples.	Triple point set tuples.	Supermatching affinity measure.	Robust under scaling, rotation and translation.	Surface color information data, articulated shape synthetic data, isometric deformable surface data are used.	Increasing the order of points, increase both accuracy and running time cost. **Future work:** Random sampling may be tried to execute in parallel .This approach can be extended to 3D data matching.

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