

Curvature Bag of Words Model for Shape Based Recognition and Image Retrieval

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ABSTRACT: Shape recognition and image retrieval are important applications in image processing. Thus retrieval of similar images is a challenge. Object shape recognition of non-rigid transformations and local deformations is a difficult problem. A shape recognition algorithm based on the curvature bag of words (CBoW) model is used to solve that problem. Object shape recognition algorithm uses a multi-scale curvature integral descriptor combine with the bag of words model to achieve shape recognition and support vector machine(SVM) is used for classification in shape recognition. For image retrieval to improve the performance of the system. The proposed method uses deep learning for retrieving images use the concept of middle level descriptor based on curvature bag of words model which extracts the convolutional features automatically. In addition an extra curvature bag of words features is added and to achieve better shape approximation and it improves the performance of the system.

KEYWORDS: Shape; Image retrieval; Shape descriptor; Shape recognition, Curvature bag of words model, Convolutional Neural Network

I. INTRODUCTION

Image processing is the technique for enhancing the pictorial data for human understanding and changing the way of an image in to additional appropriate way for autonomous machine observation. Applications of image processing and analysis techniques, which can be useful in many fields like shape recognition, signature recognition, face recognition, image retrieval, shape recognition. Shape recognition is the process of identifying and detecting an object or a feature in a digital image or video. Applications like systems for factory automation, toll booth monitoring, and security surveillance. There are different types of recognition, mainly pattern recognition, object recognition Most commonly based on shape feature, shape is an inherent feature in understanding an image that remains stable in-spite of changes in an objects illumination, colour, and texture.

Shape-based object recognition is generally considered to be a classification problem that classifies the tested objects shape through a given set of shapes. The general process of the traditional object recognition algorithm is as follows: To assess the objects shape, first, the shape feature descriptors are extracted. Then, a matching algorithm is applied to obtain the distances between the descriptors. Finally, the shape recognition classification is completed by sorting and metric learning. During this process, the shape-distinguishing ability of the descriptor directly affects the recognition result; thus, most shape recognition work has concentrated on descriptors.

Most shape recognition work has concentrated on descriptors, the contour based shape representation method uses a set of points extracted along the shape boundary curve to describe the shapes features, which can be more suitable for shape recognition and retrieval. In shape recognition and image retrieval, features or description extraction is an important approach. Features may visual based and text based. There are several features and different techniques are used to perform shape recognition and retrieval tasks.

The proposed system uses a Convolutional Neural Network for image retrieval. An image retrieval is one of the significant research area which can be used for browsing, searching and retrieving images from a large database of digital images. Image retrieval improves the efficiency of the system than recognition.

The rest of the paper is organized as follows: section 2, the survey on the various shape recognition methods. In section 3, the proposed method is presented. The experimental setup is presented in Section 4. Result Analysis are presented in Section 5. Section 6, concludes the research.

II. RELATED WORK

Arbelaez et al.[1], proposed two fundamental problems are contour detection and image segmentation. State-of-the-art algorithms are used in both tasks. Combines contour detector and multiple local cues into a globalization frame work, it is based on spectral clustering and segmentation algorithm. The segmentation algorithm consists of generic machinery for transforming into a hierarchical region tree. In this manner, reduce the problem of image segmentation of contour detection. Extensive experimental evaluation demonstrates that both contour detection and segmentation methods significantly outperform competing algorithms. The automatically generated hierarchical segmentation can be interactively renewed by user specified annotations.

R. Hong et al.[2], proposed an algorithm using colour information in the HSV colour space obtain the pixel of the object which implements image segmentation, and implements edge detection to recognize the object by using this pixel. The experimental result shows that this algorithm can recognize the object exactly in the different illumination conditions and satisfy the requirement of the competition.

S. Belongie et al.[3], proposed a shape detection method using a feature called shape context. It is descriptive of the shape of the object, thus shape context describes all boundary points of shape concerning any single boundary point. Object recognition can be achieved by matching this feature with Apriori knowledge of the shape context of the boundary points of the object.

W.Wang et al.[4], proposed by using a new descriptor and relaxation labelling technique, shape matching algorithm is developed. For each contour point, the descriptor captures the distribution of all points within the shape region along the vector perpendicular to that from the centroid to the point. In addition to stable affine invariance, the descriptor is robust to noise since it makes use of all points in the shape region. Compared to the other four state-of-the-art contour-based shape matching algorithms, this algorithm is more robust and capable of shape matching under affine transformations and noise.

F. Mokhtarian et al.[5], proposed a method for retrieving shape similarity in large image databases which is robust for noise, scale and orientation changes of the objects. It represents the shapes of object boundary contours by using Curvature Scale Space (CSS). Then the matching algorithm has been designed to use global information, it is sensitive to major occlusion.

Y. Mingqiang et al.[6], proposed a new effective shape descriptor is chord context, for shape description image retrieval. It extracts attributes from both contour as well as region information without the need for special landmarks or key-points. Chord context describes a frequency distribution of chord length with different orientations and this method is unaffected by translation, rotation, and scaling.

R.Wang et al.[7], proposed the values of a geometric characteristic of toe images based on the toe shape description method. Corner detection is carried out on toe region, and the characteristic points which can describe the toe shape are confirmed by the edge of the toe image. Through finding characteristic points then distances to the centre are stable and it can distinguish different toe shapes and the correlation among them.

H. Ling et al.[8], proposed the inner-distance is defined as the length of the shortest path between landmark points within the shape silhouette and build shape descriptors that are robust to articulation. It shows articulation insensitive and more effective at capturing part structures than the Euclidean distance. Three approaches are using the inner-distance, the rest method combines the inner-distance and multi-dimensional scaling (MDS) to build articulation invariant signatures for articulated shapes. The next second method uses the inner-distance to build a new shape descriptor based on shape contexts and the third one extends the second one by considering the texture information along the shortest paths.

B. Wang et al. [9], proposed retrieval of leaf images by using the shape description method. In this method multi-scale arch height (MARCH), hierarchical arch height features at different chord spans are extracted from each contour point to provide a compact, multi-scale shape descriptor, and leaf shape can be effectively captured. The experimental result achieves higher classification rate and retrieval accuracy.

E. Moomivand et al.[10], proposed a method in which the main property of shape (centroid) is considered as a basic point for recognition. Then, two structural properties such as distance and angles between the centroid and shape contour are calculated. At last, combining these two structural features and new Feature Space is constructed. The proposed shape descriptor can measure periodical, and symmetry of shapes.

L.Nanni et al.[11], proposed a method based on the local phase quantization matrix description to improve the retrieval performance of traditional descriptors, such as the shape context, inner-distance shape context, and height function. For extracting features from the shape descriptors and improving the performance of the standard shape matches (ID/SC/HF).

M.Cui et al. [12], proposed the curvature of the curve and unsigned curvature integral to provide a curve descriptor, which samples the contour curve using the same curvature integral so that the sampling points are more concentrated on the curve, and the descriptor has a larger entropy value. Although the algorithm was a significant improvement for computational complexity and can match occluded objects, its descriptor is susceptible to noise.

Donggang Yu et al.[13], proposed a novel and effective method of shape analysis and recognition based on skeleton and morphological structure. A series of pre-processing algorithms, smooth following, liberalization are introduced and a series of morphological structural points of image contour is extracted and merged.

J.Almazan et al.[14], proposed a novel feature extraction technique, that uses an on rigid representation adaptable to the shape. This method employs a deformable grid based on the computation of geometrical centroids that follows a region partitioning algorithm. The result is a shape descriptor that adapts its illustration to the given shape and encodes the pixel density distribution.

Yang et al.[15], proposed a multi-scale descriptor for shape matching and object recognition. The descriptor includes three types of invariants in multiple scales, to capture shape features from discriminative local, semi-global. Shape matching is employed by using a dynamic programming algorithm. The experiment results yield shape feature is invariant to translation, rotation, scaling and well tolerate partial occlusion.

X.Zhang et al.[16], proposed a multi-scale ellipse descriptor (MED) method for shape description and matching. MED extracts the features of shape contour by measuring the spatial location relationship between sample points and topology structure information of the segmented multi-scale zone. This method is effective and efficient.

X.Wang et al.[17], proposed mid-level modelling of shape representation and It focuses on designing low-level shape descriptors that are robust to rotation, scaling and deformation of shapes. Bag of Contour Fragments (BCF) is the new shape representation, inspired by classical Bag of Words (BoW) model. In BCF, a shape is decomposed into contour fragments and described by using a shape descriptor. Finally, a compact shape representation is built by pooling shape codes in the shape. Linear SVM classifier is used for shape classification. BCF achieves the state-of-the-art performance on several well-known shape benchmarks.

M. R.Daliri et al.[18], proposed two algorithms based on shape recognition. Each is map the contour of the shape to be recognized into a string of symbols. The first algorithm relies on supervised learning using string kernels. The second algorithm relies on weakly supervised on the Procrustes analysis and on the edit distance used for computing the similarity between strings of symbol.

JiexianZeng et al.[19], proposed a shape recognition algorithm based on the curvature bag of words model to solve that problem. First, object contour is obtained by using the discrete contour evolution algorithm. Next, based on the shape contour is decomposed into contour fragments. Then, this model is used to represent the contour fragments. Finally, a linear support vector machine used to classify the shape feature descriptors. By using these feature descriptors shape can be recognized.

III. PROPOSED SYSTEM

This system represents two types of applications they are shape recognition and image retrieval system. First shape recognition, It is based on curvature bag of words (CBoW) model. Image Retrieval system is used for the searching of relevant images in various research areas. The overall architecture is image retrieval based on the middle level curvature integral descriptor and shape recognition. There are different descriptors used in shape recognition. Here curvature is used as descriptor. The curvature descriptor is encoded to break through the limitation of the correspondence relationship of the sampling points for shape matching and it forms the feature of middle level semantic description. The equal curvature integral ranking pooling is employed to enhance the feature discrimination and improves the performance of the middle level descriptor. By using Convolutional Neural Network (CNN) for retrieving images

3.1 Shape Recognition

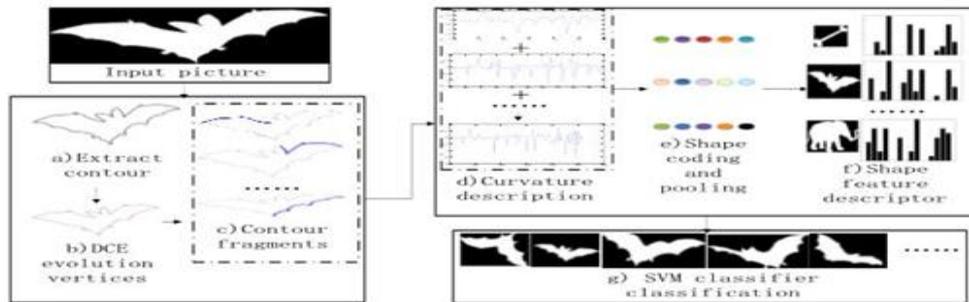


Fig 3.1:Flowchart for shape recognition .(Image courtesy [19])

It shows algorithm flowchart of the shape recognition based on curvature bag of words (CBoW) model, which includes the following steps:

- Extract the object contour by using the contour extraction algorithm.
- Approximate the polygon of the object contour by applying the discrete contour evolution (DCE) algorithm .
- Decompose the shape contour in to the contour fragments by using the vertices of the polygon.
- Sample the contour fragment with the same curvature integral by applying different scales, calculating the curvature and obtaining the curvature description of the curve.
- Code each contour fragment with the locality- constrained linear coding (LLC) algorithm, and use the max-pooling method to obtain the shape feature description.
- The shape feature descriptor obtained after previous step.
- Classify the shape feature descriptor by using the linear support vector machine (SVM).

3.1.1 Image Retrieval

For image retrieval we can use the concept of curvature descriptor based on bag of words model using support vector machine (SVM) classification algorithm and shape can be recognized. Finally, by using Convolutional Neural Network (CNN) algorithm is used for retrieving images and then improves the performance of the system. It shows the system architecture for image retrieval

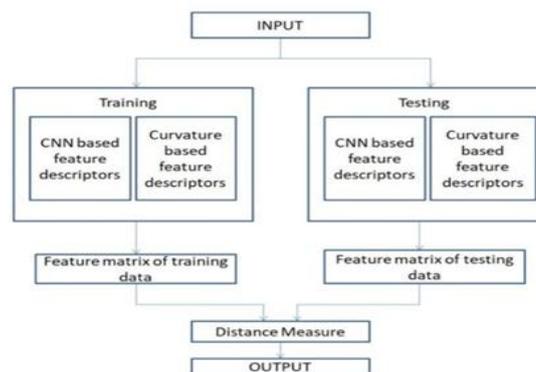


Figure 3.1.1: System Architecture For Image Retrieval

The system represents architecture for image retrieval it shows 2 phases of image retrieval system. They are training and testing phase. In training phase first CNN based feature descriptors can be extracted and curvature based feature descriptors then both are concatenate. In testing phase same as above features like CNN based feature descriptors can be extracted and curvature based feature descriptors then both are concatenate. Then distance calculated of both features of training and testing phase distance calculated and find the closest images, that images can be retrieved.

3.1.2 Shape Recognition based on CBOW model

Shape-based object recognition is generally considered to be a classification problem that classifies the tested objects shape through a given set of shapes. Most shape recognition work has concentrated on descriptors like Feature Extraction

1. Contour Decomposition

The purpose of the contour decomposition is to decompose the contour of the object in to contour fragments. For binary images, the contour extraction algorithm is first applied to extract the object contour. Then, the DCE algorithm is used to obtain the approximate polygon of the objects contour. Finally, the vertices of the polygon are applied to decompose the shape contour into contour fragments.

2. Contour Extraction

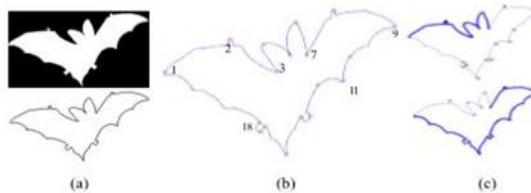


Figure 3.1.2.2 Target contour decomposition.(a) Target and contour; (b) DCE vertices;(c) cij and cji. (Image courtesy [19])

The contour extracted by the edge detection method (such as the canny operator) will retain some noise and cause some data information to be lost. The contours extracted by the morphological operator also retain some background noise and distort objects. The contour method can obtain more complete and ideal object contours and remove interference from noise in complex backgrounds.

3. DCE Evolution Vertex

Assume that the objects shape contour is S , and we represent the shape contour S as $S(u) = (x(u), y(u))$. Then, we use the DCE algorithm to obtain a simplified polygon.

$$\vec{p} = (p_1, \dots, p_T). \quad (1)$$

The representation shown in (1) where T is the number of vertices, which is determined by parameter of the DCE algorithm, and represents the polygon vertices on S .

4. Contour Fragments

For a given shape contour S and the vertices evolved by the DCE algorithm, the contour fragment set can be expressed as $C(S)$. $C(S)$ consists of the segments between each pair of vertices (p_i, p_j) . Suppose that c_{ij} represents a contour segment between p_i and p_j . Then, we have the following:

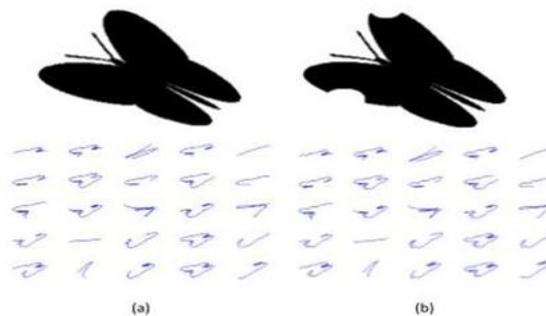


Figure 3.1.2.4 Part of the butterfly profile.
(a) Complete butterfly picture and outline fragments;
(b) Local deformed butterfly picture and contour fragment

Fig. 3.1.2(c) shows the contour segments of the vertices (1, 7) and vertices (7, 1). Because the contour fragment between all the vertices are extracted, $C(S)$

$$C(S) = \{c_{ij} = (p_i, p_j); i \neq j; i, j \in [1, \dots, T]\}. \quad (2)$$

It contains information on the very rich shape contours in S . As shown in Fig 3.3.4, shows all the contour fragments extracted from one shape can effectively avoid differences caused by local deformations, and extract the same contour fragment that does not contain the deformation.

5. Curvature bag of words (CBoW) model

The bag-of-words (BOW) model is a commonly used document representation method in the field of information retrieval. How to construct the CBoW model $f(S)$ for the shape contour segment set $C(S)$ and classify the shape by using $f(S)$.

5.1. Curvature Description

Since the point coordinates of the contour are very unstable, they change with the transformation, rotation, scale scaling of the object, thus, the point coordinates of the contour cannot be used as a stable shape characteristic. The curvature is widely used to describe shapes as a similar invariant feature. Input of the fragment c_{ij} and calculate its curvature feature descriptor x_{ij} .

$$S = c_{ij} \cup c_{ji}. \quad (3)$$

The input contour fragment (curve) c_{ij} is parameterized by formula (4):

$$\Gamma(u) = (x(u), y(u)). \quad (4)$$

Then, the formula to calculate the curvature is shown in formula (5):

$$k(u) = (\dot{x}(u)\ddot{y}(u) - \ddot{x}(u)\dot{y}(u))/(\dot{x}^2(u) + \dot{y}^2(u))^{3/2}. \quad (5)$$

To eliminate the influence of noise, the curve c_{ij} is convoluted by using a Gaussian template $g(u)$, and the curve after convolution is represented by (6): Then, the curvature of the curve 0 can be expressed as shown in (7):

$$k(u, \sigma) = \frac{X_u(u, \sigma)Y_{uu}(u, \sigma) - X_{uu}(u, \sigma)Y_u(u, \sigma)}{(X_u(u, \sigma)^2 + Y_u(u, \sigma)^2)^{3/2}}. \quad (7)$$

The curvature feature descriptor x_{ij} is calculated using the following steps ;

- To standardize the arc length, first resamples c_{ij} , and use p equidistant points, and then performs Gaussian smoothing to obtain the curve.
- Calculate the curvature k , according to (7) to obtain an S - k diagram.
- Integrate the curvature to obtain graphs of $\delta|k|$ - s and $\delta|k|$ - k .
- For the graph of $\delta|k|$ - k , use a different step size $L = (\sum k/N)$ (where N is the number of sampling points, and N/p) to sample, obtain the point set Γ_0 corresponding to the sampling curvature and calculate the curvature according to (7).
- Conduct multi-scale sampling. In order to avoid attenuating the number of sampling points too fast, this articles methods have been tested many times. Repeat step(4) t times to obtain the curvature feature descriptor:

$$x_{ij} = [k_{N_1}, k_{N_2} \dots k_{N_t}]. \quad (8)$$

Performed a Gaussian template on the curve be for calculating the curvature. Furthermore, our algorithm makes use of curvature integral multi-scale sampling on the basis of the previous two methods and because Gaussian template could be used to eliminate Gaussian noise.

5.2 Shape Coding and Pooling

There are many kinds of code book learning methods, which are mainly divided into supervised learning and unsupervised learning. Supervised learning requires training sets and testing samples, find rules in the training set and use these rules for the testing samples. Unsupervised learning requires no training set and only a set of data that looks for rules in the set of data. The unsupervised learning k-means algorithm is stable, its spectral clustering effect is good, and its hierarchical clustering is fast. Therefore, the k-means,

$$B = [b_1, b_2, \dots b_M] \in R^{t \times M} \tag{9}$$

Each column in the above formula is a cluster center, and M is the number of cluster centers. This article uses the LLC algorithm for encoding. LLC introduces local constraints and operates at a higher speed. The maximum response on each code word can be obtained by using max-pooling. Then max-pooling can be expressed as follows:

$$f(S,r) = \max(W^z | Z \in SS_r)$$

5.3 Support Vector Machine (SVM) classification

The multiclass support vector machine is used for shape classification. Given the shape training set f_i with the label $y_i \in [1 \dots H]$, H is the number of training categories. Classify the shape feature descriptor by using SVM classifier, and shape can be recognized.

3.2 Image Retrieval using Convolutional Neural Network

For image retrieval use the concept of middle level descriptor based on curvature bag of words model concatenate with convolutional features are used to achieve better performance. By using VGG16 is used for retrieving images.

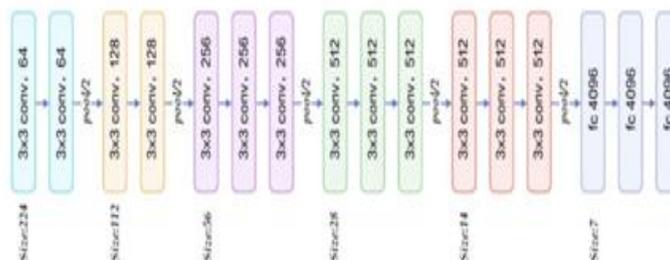


Figure 3.2:Architecture of VGG16

3.2.1 VGG16

VGG16 is a convolution neural net (CNN) architecture. It follows this arrangement of convolution and max pool layers consistently throughout the whole architecture. In the end it has 2 FC (fully connected layers) followed by a soft-max for output.

	LAYER	FEATURE MAP	SIZE	KERNAL SIZE	STRIDE	ACTIVATION
Input	Image	1	224 x 224 x 3	-	-	-
1	2 x Convolution	64	224 x 224 x 64	3 x 3	1	relu
	Max Pooling	64	112 x 112 x 64	2 x 2	2	relu
3	2 x Convolution	128	112 x 112 x 128	3 x 3	1	relu
	Max Pooling	128	56 x 56 x 128	2 x 2	2	relu
5	3 x Convolution	256	56 x 56 x 256	3 x 3	1	relu
	Max Pooling	256	28 x 28 x 256	2 x 2	2	relu
7	3 x Convolution	512	28 x 28 x 512	3 x 3	1	relu
	Max Pooling	512	14 x 14 x 512	2 x 2	2	relu
10	3 x Convolution	512	14 x 14 x 512	3 x 3	1	relu
	Max Pooling	512	7 x 7 x 512	2 x 2	2	relu
13	FC	-	25088	-	-	relu
14	FC	-	4096	-	-	relu
15	FC	-	4096	-	-	relu
Output	FC	-	1	-	-	softmax

Figure 3.2.1: Working of VGG16.

The input to conv1 layer is of fixed size 224x224 RGB image. The image is passed through a stack of convolutional (conv.) layers, where the filters were used with a very small receptive field: 3*3. In one of the configurations, it also utilizes 11 convolution filters, which can be seen as a linear transformation of the input channels. The convolution stride is fixed to 1 pixel; the spatial padding of convolutional layer input is such that the spatial resolution is preserved after convolution, i.e. the padding is 1-pixel for 3*3 conv. layers. Spatial pooling is carried out by five max-pooling layers, which follow some of the conv. layers. Max-pooling is performed over a 2*2 pixel window, with stride 2. Three Fully-Connected (FC) layers follow a stack of convolutional layers. The first two have 4096 channels. The final layer is the soft-max layer. The configuration of the fully connected layers is the same in all networks. All hidden layers are equipped with the rectification (ReLU) non-linearity. Finally features are extracted to fully connected layer from convolution layers. By using VGG16 for feature extraction procedure. After extracting features then label matrix created for a model creation, that feature matrix concatenate with curvature descriptors then both compare and by using distance measure like Euclidean distance. Distance calculated and minimum distance should be taken as retrieved images.

IV. EXPERIMENTAL SETUP

The basic system was implemented in Matlab. To verify the accuracy of the proposed algorithm, the performance of the algorithm was verified on the MPEG-7 database. To select the optimal parameter settings, five categories of pictures are selected from the MPEG-7 image library to form a small image library. We ran our experiment on PC with Intel Core i5, CPU (1.6 GHz) and 4GB RAM. First, the test is performed on the database, and then the appropriate parameter settings are selected according to the experimental results. Figure 4 shows the selected target categories



Figure 4: Image categories selected in MPEG-7.

V. RESULT ANALYSIS

We evaluate the performance of the proposed system to improve the performance of contour based image retrieval by applying curvature descriptors. The evaluation divided into two parts. The first part is to evaluate shape recognition based on curvature bag of words model and second part is to evaluate image retrieval by applying curvature feature and CNN feature concatenated and third part is image retrieval using CNN. Both cases of image retrieval can be determine the performance of the system. The evaluations are based on accuracy.



Classes	CNN Features	CNN and Curvature Features
Apple	73.33%	80%
Bottle	74%	82%
Children	70%	80%
Watch	80%	86%
Bat	78%	85%

FIGURE 5: COMPARISON OF CNN AND BOTH CURVATURE AND CNN FEATURES

In each cases of image retrieval, accuracy of concatenated CNN and curvature features is more than CNN features then it improves the performance of the system then in shape recognition accuracy is 80 percentage, then in image retrieval should be more efficient than recognition. Both accuracy compared in the case of image retrieval accuracy of concatenated of CNN and curvature feature is more than image retrieval using CNN

Here the observed result shows improve the performance of contour based image retrieval by applying curvature descriptors and CNN. Accuracy is better in the case of image retrieval. Then the system is more efficient in image retrieval than recognition.

VI. CONCLUSION

This system represents two types of applications they are shape recognition and image retrieval system. For shape recognition the algorithm uses middle level descriptors based on curvature bag of words model and SVM classifier is used for classification and shape can be recognized. For image retrieval using middle level descriptor based on curvature bag of words model and image retrieval using CNN and both features concatenate that is CNN and curvature features. In image retrieval both cases compares and more accuracy in concatenated both features, then features are increased it increases the accuracy and it improves the performance of the system.

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