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Shape Matching For Shape Descriptors Using Support Vector Machine Technique and SIFT Algorithm

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Abstract*—In the present scenario shape matching plays a very crucial role in a daily life. Whenever there is a matter of security basis shape matching becomes very essential and a must. Approach for learning based shape descriptor for shape matching is manifested. Articulated in a Bag-of-Words (BoW) like framework, the local features extracted from certain shape to generate an incorporated representation. It bestows to the speed-up of shape matching, since in the vector space analysis, distance metric can be directly applied to compare the constructed global descriptors, which decimates the time consuming stage of local feature of matching. An Efficient shape descriptor like SIFT formulated by the Bag-of-Words (BOW) framework is proposed in this project. Based on the appearance of the object SIFT features are local at the particular points of interest. The SIFT features are comparatively easy to extract and allows correct object identification with less probability of mismatch. SIFT features are invariant to image scale, rotation and robust to changes. Shape classification with bag of visual words only requires efficient linear SVM classifier for 2D images. A local contour based feature extraction method is designed for 2D shapes, which helps in incorporating both local and global information of images retrieval.

***Index Terms*—:** **Bag of visual words (BoW). Shape Matching, SIFT, SVM (SupportVectorMmachine).**

I. INTRODUCTION

In computer vision shape matching is a fundamental problem with many applications like shape retrieval, object recognition, animation synthesis, gesture synthesis robot navigation, and gesture recognition. Shape is an intrinsic feature for image apprehension, which is stable for and variations in object color and texture and illumination. shape is broadly considered for object recognition, Because of these advantage .In particular, with the recent advance in contour detection ,shape based object recognition in natural image is becoming more practical and attracts more attention in computer vision community. Main challenges in shape based object recognition include occlusion, deformation and view point change of objects. The mechanism for shape matching of our human beings is undecipherable, but it is obvious that the previous methods have a large gap with the level of human beings in both recognition accuracy and computational efficiency.

One of the most important problems in the current shape analysis community is to obtain a meaningful shape similarity/dissimilarity measure which, when comparing two shape instances, that can be applied to magnanimous-scale shape matching scenarios. Various shape descriptors have been proposed to address these challenges. Shape based object recognition is usually considered as a classification problem. Given a set of training shapes and category label of each training shape, we need to determine which category a testing shape belongs to. However, conventional pair-wise matching based approaches may not always provide a close similarity measure for shape comparison, which is capable of dealing with impingement such as large intra-class variations, non-rigid deformation, and part occlusion. These approaches as they somehow ignore the structure of the underlying data Manifold, will often encounter limitations. Recently there are ontogeny interests in unsupervised learning a context sensitive similarity. These methods manifest that exploring the context between all the instances of the database can lead to an admirable similarity measure, which significantly improves the retrieval/recognition performance.

The previous works on shape similarity measures can be coarsely divided into two categories: the pair-wise similarity measure, and the context-based similarity measure. By designing some smart shape descriptors with

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enough discriminative power or making an effort to establish the robust correspondence the pair–wise similarity measure computes the matching cost between a given pair of shapes. The context-based similarity measure enhances the given similarities by exploring the similarity context between all the database instances. Apparently, the approaches in the second category usually work well based on the output shape similarity measure of that in the first category.

For every training shape ,the correspondences between its shape descriptors and the shape descriptors in the testing shape is found using matching algorithms ,such as SIFT algorithm; then the matching costs is computed according to the matching results; finally ,training shapes are based on the matching costs and classify the testing shape using the nearest neighbor(NN) classifier. This exemplar-based shape classification strategy has been widely used in today's world in day to day life. Thus, our goal is to construct an informative shape representation in the proposed method. Given a segmented shape (or a binary image), we decompose its outer contour into several contour fragments, which are our basic shape descriptors for learning the shape codes (or a shape vocabulary).

II. LITERATURE SURVEY

The key issue about 2D shape matching is to find an effective representation of corresponding shape, with limited information (typically a binary mask) in hand. Traditional 2D shape representation methods mainly follow two trends:

- Local feature based representation and
- Global feature based representation.

Local feature based methods aim at using a set of local features to describe certain shape and most of them are contour based descriptors.

[1]: *A Novel Method for Image Corner Detection Based On the Curvature Scale-Space (CSS) Representation*

In this paper the first step is to extract edges from the original image using a canny detector (1986). The corner points of an image are defined as points where image edges have their maxima of absolute curvature. The corner points are detected at a high scale of the CSS and tracked through multiple lower scales to improve localization. This method is very robust to noise, and we believe that it performs better than the existing corner detectors An improvement to Canny edge detector's response to 45° and 135° edges is also proposed. Furthermore, the CSS detector can provide additional point features (curvature zero-crossings of image edge contours) in addition to the traditional corners.

[2]: A Novel Approach To Measuring Similarity between Shapes and Exploit It for Object Recognition

In our framework, the measurement of similarity is preceded by: 1.Solving for correspondences between points on the two shapes.2Using the correspondences to estimate an aligning transform. In order to solve the correspondence problem, we attach a descriptor, the shape context [8], to each point. The shape context at a reference point captures the distribution of the remaining points relative to it, thus offering a globally discriminative characterization. The dissimilarity between the two shapes is computed as a sum of matching errors between corresponding points, together with a term measuring the magnitude of the aligning transform.

[3]: Bag of contour fragments for robust shape classification

Shape representation is a fundamental problem in computer vision. Current approaches to shape representation mainly focus on designing low-level shape descriptors which are robust to rotation, scaling and deformation of shapes. In this paper, we focus on mid-level modeling of shape representation. We develop a new shape representation called Bag of Contour Fragments (BCF) [5], [7], inspired by classical Bag of Words (BoW) model. In BCF, a shape is decomposed into contour fragments each of which is then individually described using a shape descriptor, e.g., the Shape Context descriptor, and encoded into a shape code. Finally, a compact shape representation is built by pooling shape codes in the shape. Shape classification with BCF only requires an efficient linear SVM classifier.

[4]: Shape matching and object recognition using shape contexts

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The goal is to develop an effective retrieval system. This paper proposes Co-Transduction algorithm that is a shape based image retrieval algorithm [6], [9], which is to combine different similarity measures for robust shape based image retrieval through a semi supervised learning framework. The accuracy of adopted similarity measures (distances or metrics) decides the performance of a retrieval system. In shape based image retrieval, intra-class shapes should have smaller distances than inter-class shapes. Given two similarity measures and a query shape, the algorithm iteratively retrieves the most similar images using one measure and assigns them to a pool for the other measure to do a reranking, and vice versa.

III. PROPOSED METHODOLOGY

In this paper we propose an algorithm for shape matching using SIFT for extracting local features in an image and Harris corner detection is used to extract corner features of each and every corner points. Bow is used for feature extraction and visual words detection. High level global features are built by using Bow. Linear SVM is used for classification of objects. Experimental results are performed on globally accepted database CALtech using mat lab software.

Image Classification with Bag of Visual Words: The process generates a histogram of visual word occurrences that represent an image. These histograms are used to train an image category classifier. The steps below describe how to setup the images, create the bag of visual words, and then train and apply an image category classifier.

Step 1: Set Up Image Category Sets

Organize and partition the images into training and test subsets. The image Set function is used to organize categories of images for training an image classifier. Organizing images into categories makes handling large sets of images much easier. Separate the sets into training and test image subsets.

Step 2: Create Bag of Features

Create a visual vocabulary, or bag of features, by extracting feature descriptors from representative images of each category.

The bag of Features object defines the features, or visual words, by using the ***k-means clustering*** algorithm on the feature descriptors extracted from training sets. The algorithm iteratively groups the descriptors into k mutually exclusive clusters. The resulting clusters are compact and separated by similar characteristics. Each cluster center represents a feature, or visual word.

We can extract features based on a feature detector, or you can define a grid to extract feature descriptors. The grid method may lose fine-grained scale information. Therefore, use the grid for images that do not contain distinct features, such as an image containing scenery, like the beach. Using speeded up robust features (or SURF) detector provides greater scale invariance. By default, the algorithm runs the grid method.

This algorithm workflow analyzes images in their entirety. Images must have appropriate labels describing the class that they represent. For example, a set of car images could be labeled cars. The workflow does not rely on spatial information or on marking the particular objects in an image. The bag-of-visual-words technique relies on detection without localization.

Step 3: Train an Image Classifier with Bag of Visual Words

The train Image Category Classifier function returns an image classifier. The function trains a multiclass classifier using the error-correcting output codes (ECOC) framework with binary support vector machine (SVM) classifiers. The train Image Category Classifier function uses the bag of visual words returned by the bag of Features object to encode images in the image set into the histogram of visual words. The histograms of visual words are then used as the positive and negative samples to train the classifier.

1. Use the bag of Features encodes method to encode each image from the training set. This function detects and extracts features from the image and then uses the approximate nearest neighbor algorithm to construct a feature histogram for each image. The function then increments histogram bins based on the proximity of the descriptor to a particular cluster center. The histogram length corresponds to the number of visual words that the bag of Features object constructed. The histogram becomes a feature vector for the image.

2. Repeat step 1 for each image in the training set to create the training data.

3. Evaluate the quality of the classifier. Use the image Category Classifier evaluate method to test the classifier against the validation image set. The output confusion matrix represents the analysis of the prediction. A perfect

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classification results in a normalized matrix containing 1s on the diagonal. An incorrect classification results fractional values.

4: Classify an Image or Image Set: Use the image Category Classifier predicts method on a new image to determine its category.

BLOCK DIAGRAM OF PROPOSED METHODOLOGY

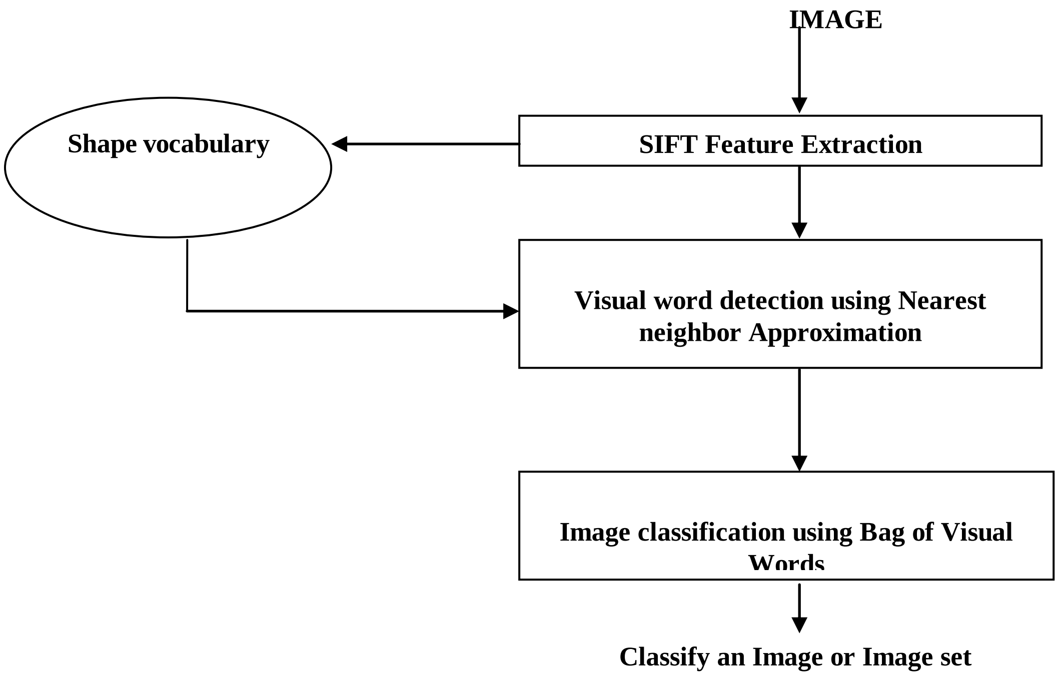

Fig 1: block diagram of proposed methodology

IV. RESULTS AND DISCUSSIONS

The proposed work is implemented on MATLAB platform. The database images are trained and tested using KNN search algorithm. Multi SVM is used for image retrieval and Category classification is identified. This experiment is also performed on Caltech dataset which comprises of 200 images in each category with different orientation, color sizes and shapes. Segmentation is applied to this database in order to extract the contour features of image thereby minimizing the search space. From the new set of segmented dataset fifty random images from every subject is used for training and rest of the images are entailed for testing purpose. Each of the different set is detected in a particular category of faces, aero planes, motorbikes and cars.

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Fig2: image recognition under the category of aero planes and cars using KNN search algorithm in mat lab simulation

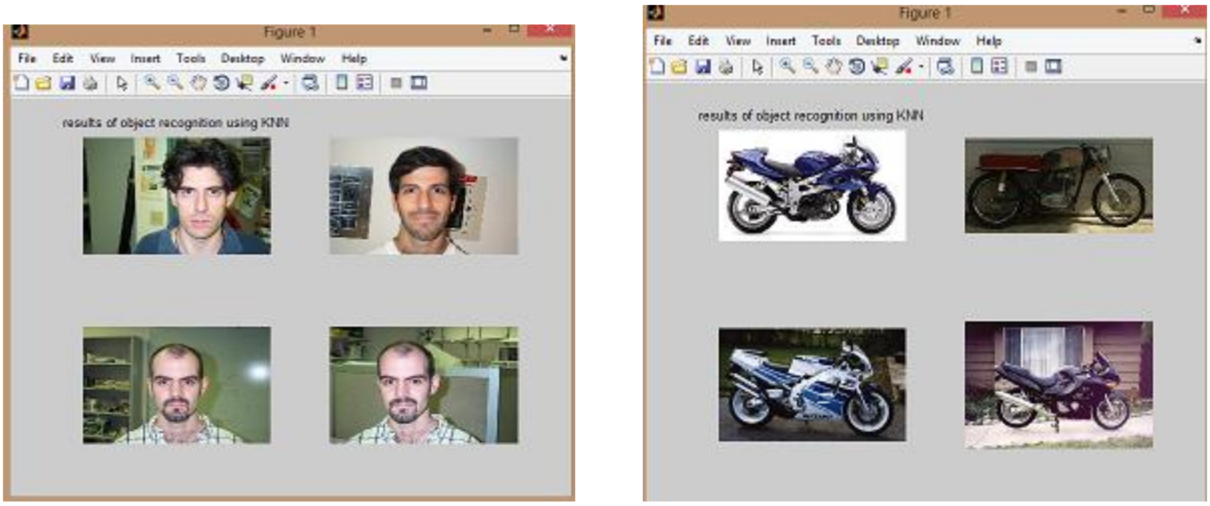

Fig3:image recognition under the category of aero Faces and Motor Bikes using KNN search algorithm in mat lab simulation.

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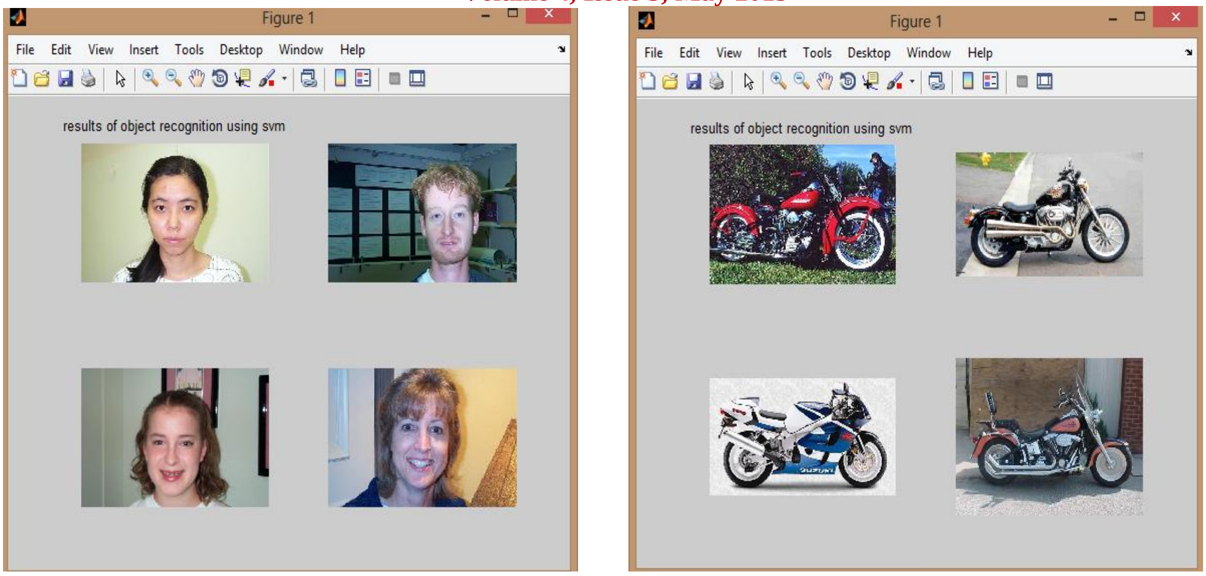

Fig:4 image recognition under the category of faces and Motorbikes using SVM in mat lab simulation

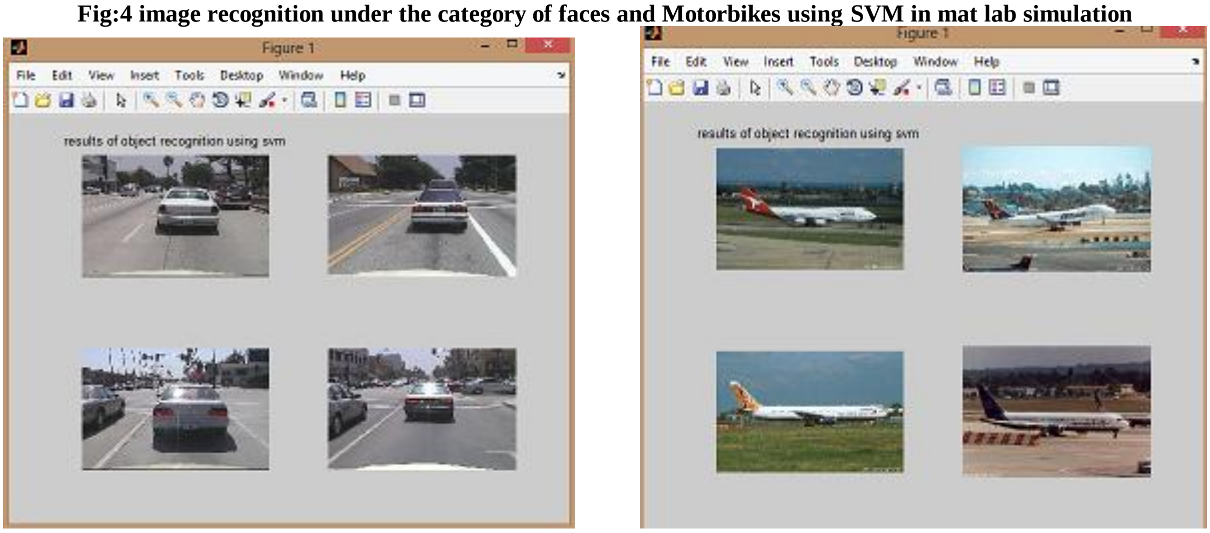

Fig 5: image recognition under the category of cars and aero planes using SVM in mat lab simulation

V. CONCLUSION

A learning based shape descriptor for shape matching is investigated. The local features extracted from certain shape to generate an integrated representation under a BoW-like framework. It contributes to the speed-up of shape

Matching, as it eliminates the time consuming stage of local feature matching. The KNN search algorithm is used for better accuracy than SVM technique.KNN search algorithm has a drawback that it has to calculate Euclidian Distance between each and every data points. Whereas SVM takes less execution time. Using SIFT algorithm and Harris corner detection features are extracted. A local contour based feature extraction method is designed for 2D shapes.

VI. FUTURE SCOPE

In the proposed methodology, individual feature extraction and classification will not give accurate results. Shape matching cannot be done for unknown classification other than images or categories present in database. Hence, it is only for one view object recognition. To overcome all these limitations. Proposed method can be enhanced with multi view object recognition.

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