Two-Dimensional Object Recognition using SVM-KNN augmented by local and global feature

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Abstract

The performance of the SVM-KNN as classifier for recognizing 2D objects from the image is discussed in this paper. The classifier is supported by the features extracted from the image. The feature vector proposed in this paper is a fusion of local and global features. For feature vector formation, Hu's Moment Invariant is computed to represent the image as global feature, which is invariant to translation, rotation and scaling and Hessian-Laplace detector and PCA-SIFT descriptor as local feature. Also the feature vector constructed is high-dimensional that reduces the performance of the classifier, in order to reduce the size of feature vector without losing the important features Kernel Principal Component Analysis is applied. The proposed method is experimented in MATLAB and tested with the COIL-100 and CALTECH 101 databases, for the both databases the results are shown. Also the experiment is performed on the noisy images of both the databases. To prove the efficiency of the proposed method, Neural Network model (BPN) is performed and the comparative results are given.

Keywords: Support Vector Machine, Moment Invariant, Hessian-Laplace, K nearest neighbor, Kernel Principal Component Analysis, Object Recognition

1. Introduction

Human beings are capable of recognizing an object by seeing the image or scene entirely or certain part of the scene or image. The process of assessing the entire image for recognition is referred as global feature, in case if only certain part or image patch is utilized for recognition of an object such feature is called as local feature. Human beings recognize objects by global and local image features. Among the local and global feature, local feature plays vital role in object recognition since it provides more number of important features. Object recognition is an important and promising research area in Computer Vision and in the area of image processing. Object recognition has the important applications in media filtering, fish classification, plant classification, Manufacturing sector and security systems, etc., Human beings are capable of recognizing objects through vision with great accuracy and apparently little effort, it is still unclear how this performance is achieved by the human being. Object recognition involves the process of identifying the locality of the object in the image if the object available in the image. Similarly the object detection is process of categorizing the object from unknown to known category. In this paper, both the recognition and detection are performed. First, locate the object and then name the object by comparing it with the database. The object recognition system proposed in this paper is consisting of the following modules image preprocessing, feature extraction, dimensionality reduction and recognition/ detection.

In this paper, an application for object recognition is proposed for recognizing the objects in the given image using local and global features of the image using SVM-KNN. For global features, Moment invariant is computed for the image and for the local features Hessian-Laplace blob detector is used.

Image features are generally classified into two categories they are local and global. Local features are computed based on the interest point in the image. Global features are computed based on intensity value of the entire image. Based on the literature review made, most of the work related to object recognition is based on either the local feature or global feature, only few work were considering the local and global features for object recognition.

Interest Point Detection is the major task in Local feature extraction for the process like object recognition. Interest point usually refers to the corners, blobs in an image, and they are useful in finding the local features in many solutions to computer vision problems. Based on the literature survey, the following are the familiar interest point detection methods available such as Moravec's Corner detector, Harris detector, SUSAN, Libdeberg scale selection theory, Harris/Hessian Laplacian [22], MSER [21] , SIFT [18], and SURF [3]. From the above methods, Mikolajczyk and Schmid [22] proposed the Hessian Laplace detector for interest point detection is scale invariant and detects blob like patches in the image.

Ahmed et.al, states that the importance of the SIFT keypoints in object identification [1]. J.Gao et.al, suggests the nearest neighbor is the best method for classifications of patterns[10].Luo Juan and OubongGwun suggests PCA-SIFT plays significant role in extracting the best features for image deformation [19]. LiLi et.al, proves that the kNN is easier and simpler to build an automatic classifier [15].Dudani et.al, shows that moment invariants plays vital role in aircraft identification [8]. Borji and Hamidiutilizes Support Vector Machine for recognition of Persian Font Recognition [4]. Chun-Jung et al. suggests Moment Invariants as feature for airport pavement distress image classification [6].

Rajesekaran and VijayalakshmiPai proved the use of moment invariant as feature extractor for ARTMAP image classification [27]. Krishna et al. uses the support vector machine with the local features for classifying the leaf images [14]. Xin-Han et al. suggests that the support vector machine performs well in identifying micro parts [30]. DanielRaja et al. uses the moment invariants and Gray level co-variance matrix for the war scene classification [7].

X.Heet al. applies different classifier for global feature and local feature. In his paper he used haar-like feature as local feature and edge feature as global. He proposes that the local features plays important in license plate detection from a video [12]. Lowe D.G. proposed the Scale Invariant Feature Transformation (SIFT) descriptor which is invariant to rotation, scaling, and translation, it provides good results in detecting previously learned objects in cluttered environment with changes in pose and with partial occlusion [18].

Hafiz T. Hasan et al. constructed a Back Propagation Neural Network for intelligent object detection. He proves BPN provides efficient and accurate results. Also he suggests Principal component Analysis (PCA) is useful only if accuracy is attained higher than the mere neural network [11]. Shih-Wei Lin et al. shows in his paper, that BPN can be applied to classify the irregular shapes, also he states with a small number of training iterations, the BPN showed fast and highly accurate classification ability[29]. Qisong Chen et al. opted KPCA as feature extraction tool for time series prediction using SVM. In his results he states that the KPCA out performs well compared to the traditional methods [26]. Ling Li Jiang et al. used KPCA as rotating machinery feature vector dimensionality reduction with Gaussian Kernel as kernel function for rotating machinery fault diagnostic case [17]. L.J.Cao et al. compares PCA, KPCA and ICA for dimensionality reduction in support vector machine, in their result with a conclusion of among other dimensionality reduction methods, KPCA provides best performance [5].

From the literature review, it is proposed to use both the local feature and global feature for the detection of the objects in the image. KPCA as dimensionality reduction tool for reducing the number features required for the processing. Also in this paper new sort of classifier is constructed to hybrid the KNN and SVM [31].

The rest of the paper is given as follows. Section 2 describes the steps involved in the construction of feature vector. Section 3 gives an overview of recognition methods. Section 4 presents discusses the proposed method. Section 5 discusses the results obtained. Finally, section 6 concludes the paper with a brief discussion of future research.

2. Feature Vector Construction

Generally the important task of object recognition model is to convert the image to feature. The process of converting the given data into classifier required format is called as Feature Extraction. In this paper, two types of features are used, first one is local feature i.e., hessian-laplacian operator as interest point detector and PCA-SIFT is used as descriptor for extracting the local features from the given image. The second feature is global feature; the most familiar global feature is Hu’s Moment invariant. The remaining part of the section addresses the global and local feature.

2.1 Geometric Moment Invariants

For the past 5 decades, moment invariant plays vital role in object recognition and pattern recognition applications. During 1970, the geometric moment invariant was introduced by Hu’s based on the theory of algebraic invariants. Since its inception, it appears to be the most promising and effective feature in representing an image. From the moment the image may be re-constructed. The set of seven moment invariant introduced by Hu’s is invariant to rotation, scaling and translation. A set of distinctive features computed for an object must be capable of identifying the same object with another possible different size and orientation. Moment Invariants holds one such set of descriptors which can be used to recognize the object even the object has change in transformations. The moment function from Eq.3-9 can act as a representative function of an image.

The two-dimensional geometric moment (m) of order (p+q)th of a function f(x,y) is defined as

$$m_{pq} = \int_{a1}^{a2} \int_{b1}^{b2} x^p y^q f(x, y)\, dx\, dy . \qquad (1)$$

where p,q = 0,1,2,……∞ and x,y gives the location of the pixel in the image along x-axis and y-axis respectively and f(x,y) gives the intensity value at a particular location. Note that the monomial product xpyq is the basis function for this moment definition. A set of n moments consists of all mpq's for p + q ≤ n, i.e., the set contains ½(n+1)(n+2) elements.Using non-linear combinations of geometric moments, Hu derived a set of invariant moments, which has the desirable properties of being invariant under image translation, scaling and rotation.

The Moment invariants are very useful way for extracting features from two-dimensional images. Momentinvariants are properties of connected regions in binary images that are invariant to translation, rotation and scale.

The normalized central moments Eq.2, denoted by η_{pq} are defined as

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}} . \qquad (2)$$

$$where \quad \gamma = \frac{p+q}{2} + 1, \ \ p + q = 2,3,4.....$$

$$\phi_1 = \eta_{20} + \eta_{02} \qquad (3)$$

$$\phi_2 = \left(\eta_{20} - \eta_{02}\right)^2 + 4\eta_{11}^2 \qquad (4)$$

$$\phi_3 = \left(\eta_{30} - 3\eta_{12}\right)^2 + \left(3\eta_{21} - \eta_{03}\right)^2 \qquad (5)$$

$$\phi_4 = \left(\eta_{30} + \eta_{12}\right)^2 + \left(\eta_{21} + \eta_{03}\right)^2 \qquad (6)$$

$$\begin{aligned}\phi_5 = &\left(\eta_{30} - 3\eta_{12}\right)\left(\eta_{30} + \eta_{12}\right)\left[\left(\eta_{30} + \eta_{12}\right)^2 - 3\left(\eta_{21} + \eta_{03}\right)^2\right] \\ &+ \left(3\eta_{21} - \eta_{03}\right)\left(\eta_{21} + \eta_{03}\right)\left[3\left(\eta_{30} + \eta_{12}\right)^2 - \left(\eta_{21} + \eta_{03}\right)^2\right]\end{aligned}$$

$$\begin{aligned}\phi_6 = &\left(\eta_{20} - \eta_{02}\right)\left[\left(\eta_{30} + \eta_{12}\right)^2 - \left(\eta_{21} + \eta_{03}\right)^2\right] \\ &+ 4\eta_{11}\left(\eta_{30} + \eta_{12}\right)\left(\eta_{21} + \eta_{03}\right)\end{aligned} \qquad (8)$$

$$\begin{aligned}\phi_7 = &\left(3\eta_{21} - \eta_{03}\right)\left(\eta_{30} + \eta_{12}\right)\left[\left(\eta_{30} + \eta_{12}\right)^2 - 3\left(\eta_{21} + \eta_{03}\right)^2\right] \\ &+ \left(3\eta_{21} - \eta_{30}\right)\left(\eta_{21} + \eta_{03}\right)\left[3\left(\eta_{30} + \eta_{12}\right)^2 - \left(\eta_{21} + \eta_{03}\right)^2\right]\end{aligned} \qquad (9)$$

A set of seven invariants can be derived from the second and third normalized central moments. This set of seven moment invariants Eq.3 to Eq.9 is invariant to translation, rotation, and scale change.

2.2 Hessian-Laplace Detector

Interest point detection is one of the common tasks performed in image processing and computer vision. Interest Point means the blob or patch of the image, where the intensity of the object is high when compared to the background or other objects in the image. Keypoint in the 2D image are the points with high curvature, here hessian-laplace detector [22] is discussed. Blob detectors are influenced by the scale space theory rely on the differential method such as Laplacian of Gaussian (LoG), difference of Gaussian (DoG) and determinant of Hessian[16]. The interest points detected by the hessian-laplace detectors are invariant to rotation and scale changes. Keypoints are localized in space at the maxima of the Hessian determinant [16] and in scale at the local maxima of the Laplacian-of-Gaussian. Hessian-Laplace obtains greater localization accuracy in scale-space and scale selection accuracy. The Hessian matrix also called as Hessian is the square matrix of second-order partial derivatives of a function; that is, it describes the local curvature of a function of many variables. The following is the function so-called Hessian Eq.10.

$$H(x,\sigma) = \begin{bmatrix} I_{xx}(x,\sigma) & I_{xy}(x,\sigma) \\ I_{xy}(x,\sigma) & I_{yy}(x,\sigma) \end{bmatrix} \qquad (10)$$

The detector computes the second order partial derivatives I_{xx} , I_{xy} , I_{yy} for each image point and then searches for points where the determinant of the of the Hessian (11) becomes maximal:

(7)

$$\det(H) = I_{xx} I_{yy} - I_{xy}^2 \qquad (11)$$

In this paper the Hessian-Laplace blob detector is used for detecting the interest point. Once the interest point is detected the SIFT [18] is applied to extract the local features. Generally SIFT, has high dimension of 128 features for each interest point detected in the image. To reduce the number of features, PCA is utilized, that reduces the features to 36 numbers. Here in this paper, for local feature extraction PCA-SIFT descriptor is used.

2.3 Kernel Principal Component Analysis

Kernel PCA (KPCA) [28] is an improvement of traditional linear PCA in a high-dimensional space that is based on the kernel function used. Principal Component analysis is a classic linear technique in statistical analysis. Given a set of values, PCA finds eigenvalue/vector, using only second-order statistics, a smaller set where the feature are uncorrelated to each other's. Kernel principal component analysis is one of the fundamental tools for unsupervised nonlinear dimension reduction and feature extraction. It involves calculation of the eigenvalue decomposition or singular value decomposition of centered kernel data and is in search for orthogonal functions that optimize the kernel data scatter. Similar to linear PCA, it involves the following eigen decomposition [2]

$$CKC = i\sum i^T \tag{12}$$

Where, K is the kernel matrix with entries Kij = k(xi,xj), C is the centering matrix Eq.12 given by

$$C = I - \frac{1}{N}HH^T, \tag{13}$$

I is the NxN identity Matrix, H=[111…1]T is an N x 1 vector, I = [a1, a2, … aN] with ai = [ai1,…aiN]T is the matrix containing the eigenvectors and $\sum = diag(\lambda_1,...\lambda_N)$ contains the corresponding eigenvalues. To denote the mean of the Φ-mapped data by $\Phi = \frac{1}{N}\sum_{i=1}^{N}\Phi(X_i)$ and define the centered map Φ as:

$$\Phi(X) = \Phi(X) - \Phi \tag{14}$$

From the above centered map Eq.14, the kth orthonormal eigenvector of the covariance matrix is computed. Then projection of $\Phi(X)$ onto the subspace spanned by the first n eigenvectors is computed.

In this paper the kernel function used is the polynomial function as in Eq. (15):

$$k(x_{i,}x_j) = (x_i^T x_j)^p, \tag{15}$$

where p = 1 gives standard PCA.

The following are the steps involved in computing KPCA in the original space:

Compute the Kernel Matrix : Kij = K(xi,xj).

Center K.

DiagonalizeKc and normalize eigenvectors:

$$\lambda_k(\alpha^k . \quad \alpha^k) \quad = \quad 1 \tag{16}$$

Extract the k first principal components

$$\Phi(X)_{kpc}^k = \sum_{i=1}^{N}\alpha_i^k (\Phi(X_i) \quad . \quad \Phi(X)) \tag{17}$$

3. Recognition Methods

3.1 Support Vector Machine

Support Vector Machine is one of the supervised Machine Learning Technique, which was first heard during COLT-92 introduced by Vapnik, Boser, Guyon. Support Vector Machines are used for classification and regression; it belongs to generalized linear classifiers. SVM is a mostly used method in pattern recognition and object recognition. The objective of the support vector machine is to form a hyperplane as the decision surface in such a way that the margin of separation between positive and negative examples is maximized by utilizing optimization approach. Generally linear functions are used as a separating hyperplane in the feature space. For achieving better performance, several kernel functions are used such as polynomial function and radial-bias function, in this paper, polynomial function is used as kernel function. When using kernel functions, the scalar product can be implicitly computed in a kernel feature space.

For the proposed work, the system starts with training sample $\{(x_i, y_i)\}_{i=1}^{N}$, where the training vector is x_i and its class label is y_i. The proposed method aims to find the optimum weight vector w and the bias b of the separating hyperplane such that

$$\begin{gathered} y_i(w^T\varphi(x_i) + b) \geq 1 - \xi_i, \qquad \forall_i \\ \xi_i \geq 0, \qquad \forall_i \end{gathered} \tag{18}$$

with w and the slack variables ξ_i minimizing the cost function given below

$$\phi(w,\xi_i) = \frac{1}{2}w^T w + C\sum_{i=1}^{N}\xi_i \tag{19}$$

where the slack variables ξ_i represent the error measures of data, C is the value assigned to the errors, and $\varphi(.)$ is a kernel mapping which maps the data into a higher dimensional feature space.

3.2 K-Nearest Neighbor

In pattern recognition, the k-nearest neighbor algorithm (k-NN) is a method for classifying objects based on closest training examples in the feature space. The k-nearest neighbor algorithm is amongst the simplest of all machine learning algorithms: an object is classified by a majority vote of its neighbors (k is a positive integer, typically small). If k= 1, then the object is simply assigned to class of its nearest neighbor. The nearest-neighbor method is perhaps the simplest of all algorithms for predicting the class of a test example. The training phase is simple, ie., to store every training example, with its label. To make a prediction for a test example, first compute its distance to every training example. Then, keep the k closest training examples, where k ≥ 1 is a fixed integer. This basic method is called the k-NN algorithm. For example k=3. when each example is a fixed-length vector of real numbers, the most common distance function is Euclidean distance

$$d(x,y)=\|x-y\|=\sqrt{(x-y)\cdot(x-y)}=\left(\sum_{i=1}^{m}(x_i-y_i)^2\right)^{1/2} \qquad (20)$$

where x and y are points in Rm.

K-Nearest Neighbor algorithm (KNN) is part of supervised learning that has been used in many applications in the field of data mining, statistical pattern recognition and many others. KNN is a method for classifying objects based on closest training examples in the feature vector. An object is classified by a majority vote of its neighbors [15]. K is always a positive integer. The neighbors are taken from a set of objects for which the correct classification is known. It is usual to use the Euclidean distance, though other distance measures such as the Manhattan distance can be used.

4. Proposed Method SVM-KNN

The proposed model can improve the performance of recognition. SVM is a binary classifier; it is convenient for classification/recognition in high dimensional space and consequently suitable for image classification and object recognition.

The steps involved in object recognition is given below, for a query (i.e., when an image is given as input to the proposed method),

i. After acquiring the image, the image is pre-processed (edge detected – Canny’s edge detector) for Feature Extraction

ii. Local Feature (Hessian-Laplace and PCA-SIFT) and Global feature (Hu’s Moment Invariant) are extracted from the pre-processed image and construct the feature vector for the given image.

iii. The constructed feature vector is applied to KPCA, to reduce the number of features.

iv. In K-Nearest Neighbor stage, the nearest neighbors are identified using the distance function such as Euclidean Distance.

v. If the K neighbors have all the same labels, the query is labeled and exit; otherwise, compute the pairwise distances between the K neighbors; and construct the distance matrix.

vi. Using the kernel trick method, the distance matrix is converted into kernel matrix, later it can be applied to SVM for classification.

vii. SVM classifier is used to classify the object.

In this paper, polynomial kernel function Eq.21 is used in the SVM procedure.

$$k\left(x_i, x_j\right)=\left(x_i^T x_j\right)^p, \qquad (21)$$

where p = 1 gives standard PCA.

The proposed object recognition model is given in fig.1. In the proposed method, the given image is pre-processed to extract the edges of the object, for edge extraction canny’s edge detection method is applied. Once the edges are extracted then the Hu’s seven moment invariants are computed and for the same image the Hessian-laplace detector is applied to get the interest points in the image, from the interest points the PCA-SIFT is computed. The feature vector is constructed using the local and global features computed. The dimensionality of the constructed feature vector is reduced by applying KPCA. KNN is used to find the closest neighbors of the given image with all the available training images. If a label is found then the algorithm quits, otherwise the SVM is applied. The proposed algorithm was used to recognize the object. The results are compared to those obtained with SVM, BPN and KNN. From the results, it is indicated that the proposed classifier is superior to some other classifier.

5. Experimental Results

The proposed method of combining the local and global feature and identifying the object from the image using SVM-KNN is implemented in MATLAB 7.5 and with the images of COIL-100 database [25] and CALTECH-101 database [9]. COIL-100 database consists of images of 100 different objects

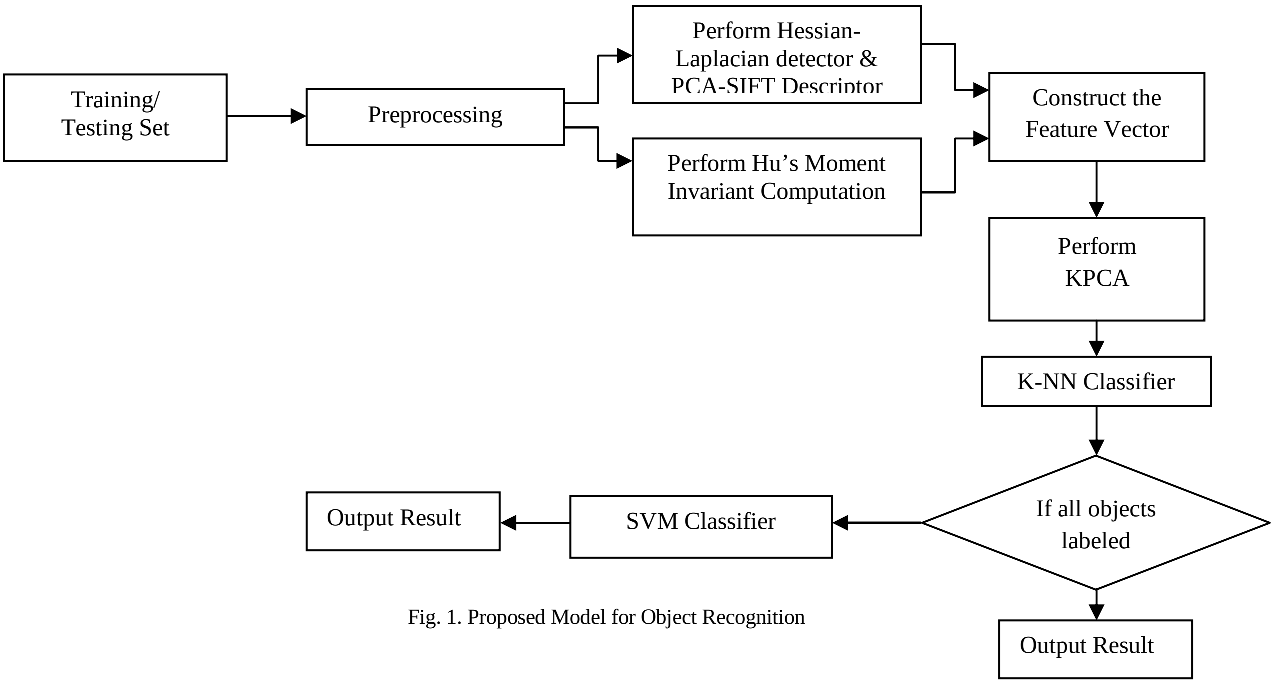

Fig. 1. Proposed Model for Object Recognition

with black background; each one is rotated with degree angle interval in vertical axis. Hence for every object there are 72 images, which sum up to 7200 images for the whole database. The CALTECH 101 dataset (L. Fei-Fei et al. [9]) consists of images of 101 object categories. The significant variation in appearance, color, and lighting makes this database challenging for object recognition and detection process. For experimenting, the set of images from the category airplanes and motorbikes are chosen. The database is classified into two parts one for testing and another one for training.

During the experimentation, the first phase is to convert the color image into gray image and perform some filtering process to remove the noise and then for the pre-processed image the canny's edge detection is performed and the edge detected image is saved for further processing. For the edge detected image the geometric moment invariants specified in Eq. 3-9 is computed and in order to compute the local feature the Hessian-Laplace detector is performed to each and every training/test image and then PCA-SIFT descriptor is computed over the interest points detected by the detector. Once local and global features are computed, they are arranged in such a way to construct the feature vector. The KPCA method is employed to reduce the dimensionality of the constructed feature vector.

The KNN classification algorithm tries to find the K nearest neighbors of x0 and uses a majority vote to determine the class label of x0, where x0 is the feature vector of the training images and test images. Without prior knowledge, the KNN classifier usually applies Euclidean distances as the distance metric. Once the KNN is performed, the query is labeled then the program ends, otherwise the kernel matrix is evaluated for the distance matrix, and then the SVM classifier is applied to the kernel matrix to label the object. This proposed method was applied to different set of training and test image sets of COIL-100 and CALTECH-101 dataset. Some of the images chosen for training and testing are given in fig.2. Table 1and fig.3 shows the performance of the proposed method compared with the traditional SVM, KNN method and Back Propagation Neural Network Model for COIL-100 dataset. Table 2 and fig.4 shows the performance of the classifiers for CALTECH-101 dataset.

Table 1Results of the classifier with different no. of Training sets for COIL-100 database

No. of Training images	**% of recognition (based on Positive recognition)**			
	25	**75**	**125**	**250**
SVM + KNN	86.20%	91%	93%	98%
SVM	80%	81.50%	79%	83%
KNN	76%	76%	73%	72%
BPN	67%	73%	74%	79%

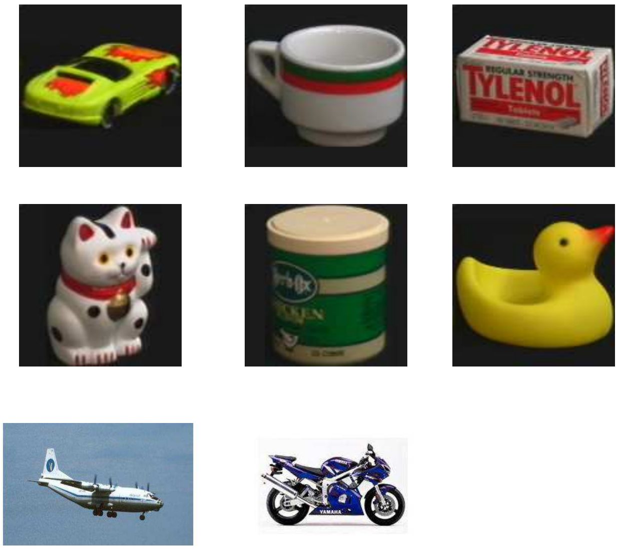

Fig. 2. First two rows are sample objects from COIL-100 and the third row consists of objects chosen from CALTECH-101

Table 2 Results of the classifier with different no. of training sets for caltech-101 database

No. of Training images	% of recognition (based on Positive recognition)			
	Aero plane		motorbike	
	50	100	50	100
SVM + KNN	87%	92%	86%	94.5%
SVM	81.2%	83%	80.4%	83.3%
KNN	74.3%	77.2%	73%	75%
BPN	70%	75%	71%	74%

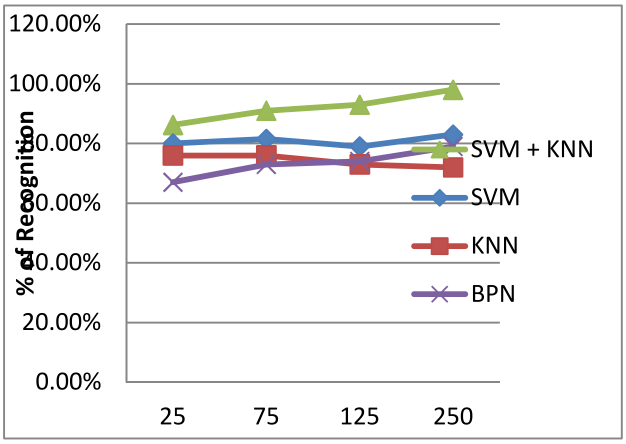

Fig.3.Performance of the proposed method for different number of training images in COIL-100.

From the above graphs fig.3 and fig.4 the proposed method outperforms the SVM, BPN and KNN.

6. Conclusion

In this paper, the object recognition system based on the combination of local and global feature is proposed. For local

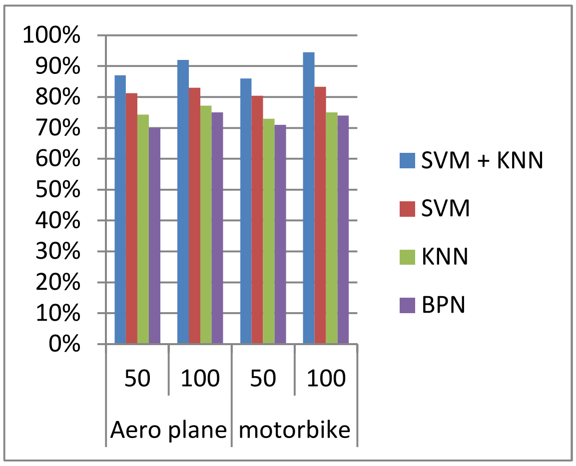

Fig.4. Performance of the proposed method for different number of training images in CALTECH-101 dataset

feature, the Hessian-Laplace detector along with PCA-SIFT descriptor is used, and for the global feature, the Hu's moment invariant which is invariant during rotation, scaling, translation is used. Also in this paper KPCA is employed as dimensionality reduction to improve the performance of the SVM-KNN classifier [24][23]. The classifier used to identify the object from the feature vector is SVM-KNN. KNN classifier is applied first to identify the closest object from the trained features, if there is no match; SVM is performed to identify the object. In the proposed method, the object recognition is done with greater accuracy. The global features and local features are robust in finding the object even the object is partially-occluded.From experimental results in the Table.1 and Table.2, it is clear that combining SVM and KNN with local and global feature reduced by KPCA can produce better results. Most of the results are even better than the traditional methods like KNN, SVM and BPN. The proposed model uses polynomial function as kernel function for both the KPCA and SVM. Future work will include the process of recognizing the 3D object based on view-based 2D images.

References

[1] Ahmed FawziOtoom, HaticeGunes, Massimo Piccardi, “Feature extraction techniques for abandoned object classification in video surveillance”, in IEEE Proceedings of the International Conference on Image processing, pp. 1368 – 1371, 2008.

[2] Alzate, C., &Suykens, J. A. K., “Kernel Component Analysis Using an Epsilon-Insensitive Robust Loss Function”. IEEE Transactions on Neural Networks, Vol.19, No.9, pp.1583-1598, 2008.

[3] Bay H, Tuytelaars T, and Van Gool L, “SURF: Speed-up robust feature”, In proceedings of European Conference of Computer Vision, pp.404-417, 2007.

[4] Borji, A.; Hamidi, M.,“Support Vector Machine for Persian Font Recognition“, World Academy of Science, Engineering and Technology, Vol.28, pp.10 – 13, 2007.

[5] L.J. Cao, K.S. Chua, W.K. Chong, H.P. Lee, Q.M. Gu, "A comparison of PCA, KPCA and ICA for dimensionality reduction in support vector machine", Neurocomputing, Vol.55, No.1-2, pp.321-336, 2003.

[6] Chun-Jung Hsu; Chi-Farn Chen; Chau Lee; Shu-Meng Huang, “Airport Pavement Distress Image Classification Using Moment Invariant Neural Network“, CRISP, pp. 123 – 127, 2001.

[7] Daniel Madan Raja, S, Shanmugam, A., “Artificial Neural Network Based War Scene Classification using Invariant Moments and GLCM Features : A Comparative Study”, International Journal of Engineering Science and Technology, Vol.3,No.2, pp. 1189 – 1195, 2011.

[8] S. Dudani, K. Breeding, R. McGhee, “Aircraft Identification by moment Invariants,” IEEE Transactions on Computers, Vol.26. No.1, pp. 39 – 45, 1977.

[9] L. Fei-Fei, F. Fergus, and P. Perona. "Learning generative visual models from few training examples: an incremental bayesian approach testing on 101 object categories". In Workshop on Generative-Model Based Vision, CVPR, 2004.

[10] J. Gao, Z. Xie, and X. Wu, “Generic object recognition with regional statistical models and layer joint boosting,” Pattern Recognition Letters, vol. 28, no. 16, pp. 2227-2237, 2007.

[11] Hafiz T.Hasan, Muhammad U. Khalid and Kashif Imran, “Intelligent Object and Pattern Recogntion using ensembles in Back Propagation Neural Network”, International Journal of Electrical & Computer Sciences IJECS-IJENS, Vol.10, No.06, pp.52-59, 2010.

[12] X.He, H.Zhang, W.Jia, Q.Wu and T.Hintz, “Combining Global and features for detection of License plates in a video”, Proceedings of Image and Vision Computing, pp. 288 – 293, 2007.

[13] Hu, M.K, “Visual Problem recognition by Moment Invariant”, IRE Trans. Inform. Theory, IT-8, pp.179-187, 1962.

[14] Krishna Singh, Indra Gupta, SangeetaGupa, “SVM-BDT PNN and Fourier Moment Technique for Classification of Leaf Shape”, International Journal of Signal Processing, Image Processing and Pattern Recognition, Vol.3, No.4, pp. 67-78, 2010.

[15] LI LiLi, ZHANG YanXia and ZHAO YongHeng, “K-Nearest Neighbors for automated classification of celestial objects,” Science in China Series G-PhysMechAstron, Vol.51, No.7, pp. 916-922. July 2008.

[16] Lindeberg T, “Feature detection with automatic scale selection”, International Journal of Computer Vision, Vol. 30, No. 2, pp. 79 – 116, 1998.

[17] Ling Li Jiang, Ping Li, Si Wen Tang, “Parameter Optimization in KPCA for Rotating Machinery Feature Vector Dimensionality Reduction”, Journal of Advanced Engineering Forum, Vol.2-3, pp.755-760. December 2011.

[18] Lowe D.G, “Distinctive image features from scale-invariant keypoints”, International Journal of Computer Vision, Vol. 60, No. 2, pp. 91-110, 2004.

[19] Luo Juan and OubongGwun, “A Comparison of SIFT, PCA-SFIT and SURF,” International Journal of Image Processing, Vol.3, Issue.4, pp. 143 – 142, 2009.

[20] MalihehShabanzade, MortezaZahedi and Seyyed Amin Aghvami, “Combination of Local descriptors and Global Features for Leaf Recognition”, Signal & Image Processing : An international Journal (SIPIJ), Vol. 2, No. 3, pp.23-31, 2011.

[21] Mataz J, Chum O, Urba M, and Pajdla T, “Robust wide baseline stereo from maximally stable external regions”, British Machine Vision Conference, pp.384-396, 2002.

[22] Mikolajczyk K. and Schmid C, “Scale & affine invariant interest point detectors”, International Journal of Computer Vision, Vol. 60, No. 1, pp. 63-86, 2004.

[23] Muralidharan R, Chandrasekar C, “Object Recognition using SVM-KNN based on Geometric Moment Invariant”, International Journal of Computer Trends and Technology, Vol.1, No.3, pp.368-373, 2011.

[24] Muralidharan R, Chandrasekar C, “Combining local and global feature for object recognition using SVM-KNN”, Proceedings of the International Conference on Pattern Recognition, Informatics and Medical Engineering (PRIME 2012), pp.1-7, 978-1-4673-1039-0/12. 2012.

[25] Nene S.A; Nayar S.K; Murase H, “Columbia object image library (coil-100)”. Technical report, Columbia University, 1996.

[26] Qisong Chen, Xiaowei Chen, Yun Wu, "Optimization Algorithm with Kernel PCA to Support Vector Machines for Time Series Prediction", Journal of Computers, Vol 5, No 3, pp.380-397, 2010.

[27] Rajasekaran, S.; VijayalakshmiPai, G.A. “Image recognition using Simplified Fuzzy ARTMAP augmented with a moment based feature extractor”, International Journal of Pattern Recognition and Artificial Intelligence, Vol.14, No.8, pp. 1081-1095, 2000.

[28] Schölkopf, B., Smola, A., & Müller, K.-R., “Nonlinear Component Analysis as a Kernel Eigenvalue Problem”, Neural Computation, Vol.10 No.5, pp.1299-1319. MIT Press, 1998.

[29] Shih-Wei Lin, Shuo-Yan Chou, Shih-Chieh Chen, “Irregular shapes classification by Back-propagation neural networks”, Int J AdvManuf Technol., vol.34, No.11-12, pp.1164-1172, 2006.

[30] Xin-Han Huang; Xiang-Jin Zeng; Min wang, “SVM-Based Identification and Un-calibrated Visual Servoing for Micro-Manipulation”, International Journal of Automation and Computing, Vol.7, No.1, pp.47-54, 2010.

[31] H. Zhang, A. C. Berg, M. Maire, and U. B. Malik JitendraEecs, “SVM-KNN: Discriminative Nearest Neighbor Classification for Visual Category Recognition,” IEEE Conference on Computer Vision and Pattern Recognition, Vol. 2, pp.2126-2136, 2006.