Object Recognition Using Support Vector Machine Augmented by RST Invariants

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Muralidharan R
Rathinam College of Arts and Science

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R.Muralidharan[1], and Dr.C.Chandrasekar[2]

[1] **Assistant Professor,Department of Computer Applications, KSR College of Engineering, KSR Kalvi Nagar, Tiruchengode, Tamil Nadu 637215, India**

[2] **Associate Professor, Department of Computer Science, Periyar University, Salem, Tamil Nadu, India.**

Abstract

In this paper the support vector machine is utilized to recognize the object from the given image. The proposed method for object recognition is associated with the reduction of feature vector by Kernel Principal Component Analysis (KPCA) and recognition using the Support Vector Machine (SVM) classifier. Also in this paper the feature extraction method extracts features from global descriptors of the image. In the feature extraction process for an image, global features are extracted and formed as feature vector. For the entire training image the feature vector is generated and dimension reduction is done using KPCA. The reduced feature vector is used to train the SVM classifier. Later test images are given as input and tested the performance of the Classifier. To prove the efficiency of the SVM Classifier, Back Propagation Neural Network is used for the object recognition. From the comparison, SVM classifier outperforms.

Keywords: *Support Vector Machine, Object Recognition, Moment Inavariants, Kernel Principal Component Analysis.*

1. Introduction

Object recognition is a fundamental vision problem of identifying what is in the image, the concepts of object recognition has been applied in various fields like Manufacturing (for detecting defects/cracks in finished goods), surveillance system, optical character recognition, face recognition etc.,. The major task in object recognition is to identify if any, of an object from the set of known objects appear in the given image or image sequence. It plays an important role in Pattern recognition/classification and its key issues are whether selected features are stable and have good ability to differentiate different kinds of Objects. Object Recognition has been the focus of considerable research during the last four decades.

Hu was the first to introduce the geometric Moment Invariants which are invariant under change of size, translation, and orientation [Hu (1962)]. Since then many of the researchers had proposed moment invariants as pattern sensitive features in classification and recognition applications. Moments and functions of moments can provide characteristics of an object that uniquely represents its shape and have extensively employed as the invariant global features of an image in pattern recognition and image classification since 1960's.

[Borji (2007)] utilizes Support Vector Machine for recognition of Persian Font Recognition. [Chun-Jung Hsu (2001)] suggests Moment Invariants as feature for airport pavement distress image classification. [Rajasekaran (2000)] augmented the use of moment invariant as feature extractor for ARTMAP image classification. [Krishna (2010)] uses the support vector machine with the local features for classifying the leaf images. [Xin-Han (2010)] suggests that the support vector machine performs well in identifying micro parts. [Daniel (2011)] uses the moment invariants and Gray level co-variance matrix for the war scene classification. [Ronald (2006)] in his paper uses the support vector machine for automatic identification of impairments on eye diagram.

This paper discusses a formulation of an object recognition model in recognizing an object using Support Vector Machine. The features for the recognition are extracted from Geometric Moment Invariants and some of the image properties. During training phase the features are generated and feature vector is constructed. The constructed feature vector falls into high dimensional data, further processing of high dimensional data is a time consuming process. For reducing the dimension of the data, dimensionality reduction process KPCA [Narayanan (2009)] is applied. Through dimension reduction the support vector is created, which is provided as input to the SVM classifier to test the test image in recognizing the object.

The rest of the paper is organized as follows. Section 2 gives an overview of Moment Invariants and Kernel Principal Component Analysis. A summary of Classifier like Support Vector Machine, and Back Propagation Neural Network are given in Section 3. Section 4 gives an outline of the proposed system. Section 5 illustrates the Experimental results and section 6 for the conclusion.

2. Moment Invariants and Kernel Principal Component Analysis

2.1 Moment Invariants

Moments and moment invariants play a very important role as features in invariant pattern recognition. The approach using invariant features appears to be the most promising and has been used extensively since 1970. Its basic idea is to describe the objects by a set of measurable quantities called invariants that are insensitive to particular deformations and that provide enough discrimination power to distinguish objects belonging to different classes.

Global invariants like moment invariants are much more robust than local invariants with respect to noise, inaccurate boundary detection and other similar factors when compared to other moment Invariants. Moment invariants were first introduced to the pattern recognition and image processing community in 1962 [4], when Hu employed the results of the theory of algebraic invariants and derived his seven famous invariants to the rotation of 2D objects.

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 $x^p y^q$ is the basis function for this moment definition. A set of n moments consists of all m_{pq}'s for $p + q \leq n$, 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. However the reconstruction of the image from these moments is deemed to be quite difficult.

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

The normalized central moments (2), denoted by ηpq are defined as

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

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

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

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

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

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

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

$$\phi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})\left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right] \qquad (7)$$

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

$$\phi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] + (3\eta_{21} - \eta_{30})(\eta_{21} + \eta_{03})\left[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2\right] \quad (9)$$

2.1 Kernel Principal Component Analysis

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 others. The nonlinear version of PCA, namely Kernel Principal Component Analysis (KPCA), is able to extract the high order statistics, thus provides more information from the original data set. 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

$$CKC = i\sum i^T \quad (10)$$

Where, K is the kernel matrix with entries $K_{ij} = k(x_i,x_j)$, C is the centering matrix Eq.(11) given by

$$C = I - \frac{1}{N} HH^T, \quad (11)$$

I is the NxN identity Matrix, $H=[111\ldots1]^T$ is an N x 1 vector, $I = [a_1, a_2, \ldots a_N]$ with $a_i = [a_{i1},\ldots a_{iN}]^T$ is the matrix containing the eigenvectors and $\sum = diag(\lambda_1,\ldots\lambda_N)$ 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:

$$\Phi(X) = \Phi(X) - \Phi \quad (12)$$

From the above centered map Eq.(12), the k^{th} 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. (13):

$$k(x_i, x_j) = (x_i^T x_j)^p,$$

where p = 1 gives standard PCA. (13)

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

1. Compute the Kernel Matrix : $K_{ij} = K(x_i,x_j)$.
2. Center K.
3. Diagonalize K_c and normalize eigenvectors:
$$\lambda_k(\alpha^k \cdot \alpha^k) = 1 \quad (14)$$
4. Extract the k first principal components
$$\Phi(X)_{kpc}^k = \sum_{i=1}^{N}\alpha_i^k\,(\Phi(X_i) \cdot \Phi(X)) \quad (15)$$

3. Classifier

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 [Haykin (1999)]

$$y_i\left(w^T\varphi(x_i) + b\right) \geq 1 - \xi_i, \quad \forall_i$$
$$\xi_i \geq 0, \quad \forall_i \quad (16)$$

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

$$\phi(w,\xi_i) = \frac{1}{2} w^T w + C\sum_{i=1}^{N} \xi_i \quad (17)$$

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 Back Propagation Network

A Back-Propagation neural network (BPN) consists of at least three layers of units: an input layer, at least one intermediate hidden layer, and an output layer as shown in Fig. 1. Typically, units are connected in a feed-forward fashion with input units fully connected to units in the hidden layer and hidden units fully connected to units in the output layer. When a Back-Propagation network is cycled, an input pattern is propagated forward to the output units through the intervening input-to-hidden and hidden-to-output weights. The output of a Back-Propagation network is considered as a classification decision.
The purpose of using Back-Propagation neural network in this study is to adopt the characteristics of memorizing and referencing properties that recognize the testing 2D image feature. The input of the network is the feature information extracted from the image. And the target is the designated index of the object. When training the BPN, the input pattern (x1,x2) is fed to the network, through the hidden layers to the output layer. The output pattern is compared with the target pattern to find the deviation. These extracted features are continuously fed into a BPN and the network will self-adjust until a set of weights (V11, V12, V21, V22, y11 and y21) with specified error value. Then these weights are stored and used for recognition later on.

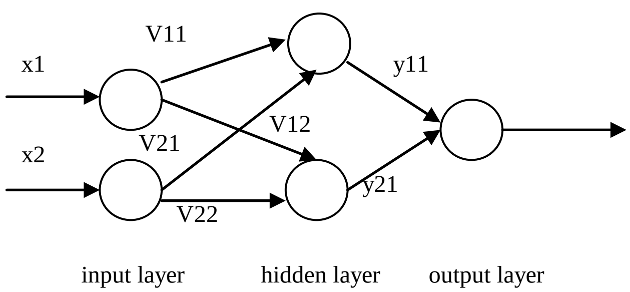

Fig. 1. Back-propagation neural networks

4. Proposed System

The proposed system for recognizing the object from an image is given below fig.2. The system is implemented as two phases. During first phase the system is trained with several set of training images. Initially the training images are preprocessed to obtain exact information for feature extraction. In the pre-processing stage, the noise in the image is removed and sharpening is done to reduce the effect of the illumination and lack of contrast on the training images. After pre-processing, the training image is applied for edge detection process, for edge detection Canny's Edge detection method is used. In the feature extraction process, the moment invariants are extracted for each of the pre-processed training images. Feature extraction is defined as a process of converting the obtained image into a unique, distinctive and compact form. The computed moment invariants for all the pre-processed training images are arranged in such way to construct the feature vector. The constructed feature vector is high-dimensional. To reduce the high dimension of the data to low dimension without losing the important properties, Kernel Principal Component Analysis is done. This results into the support vector that can be used for the classifier Support Vector Machine. During testing phase, once the test image is given as input to the proposed system, the pre-processing and feature extraction process are done as specified in the training phase. The computed feature vector is given as input to the Support Vector Machine Classifier, based on the support vector generated during training phase; the input image is recognized and labeled. To compare the results of Support Vector Classifier, the Back Propagation Neural Network is trained with feature vector and tested.

5. Experimental Results

Table 1 and Table 2 show some of the selected results of our experiments. The experiment is conducted to estimate the recognition accuracy, and to verify the robustness of the proposed method. To experiment the proposed method, COIL-100 database which is widely used in 3D object Recognition researches [Nene (1996)]. This database consists of images of 100 different objects; each one is rotated with 5 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 entire COIL-100 database is divided into two sets, one as training set and another one as test set. Three different training sets are formed for three different sampling angles (10, 30, and 50 degrees). The following fig.3 shows the set of sample images (Grayscale) used for forming the training set.

The proposed system is experimented with each set of training and test images and the results are shown in the table. The proposed method has been implemented using MATLAB. To evaluate the recognition accuracy for the proposed methods and the traditional methods the correct recognition percentages (CRP) were determined.

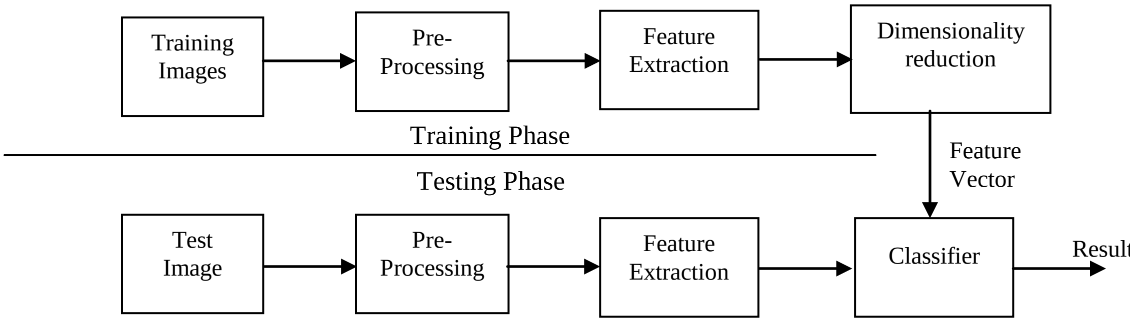

Fig.2. Schematic model of the proposed system

To verify the robustness, the proposed method is compared with performance of SVM using the original feature vector. The resultant values are shown in the table 1. and fig.4. The experiment is also conducted by increasing the number of training images. The resultant values for the increased training images are shown in the table 2. and fig.5. From the experimental results it is proved that the proposed method provides better performance in terms of CRPs compared with the traditional method. The CRP is computed as

$$CRP = \frac{Np}{T} \tag{18}$$

Where Np is number of positive recognition and T is total number of test conducted. The CRP values are provided in the table 1 and 2 and the performance is shown in the graph fig.4 and fig.5.

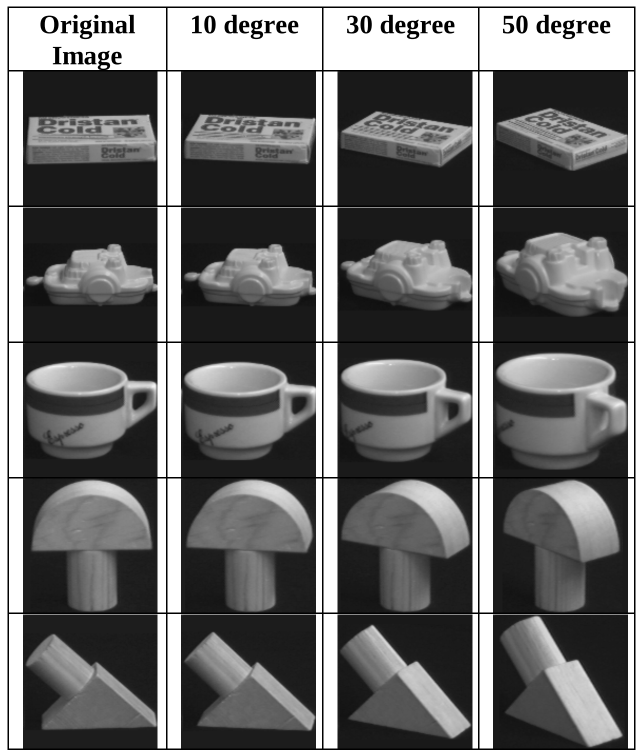

Fig.3. Sample images from COIL-100 Database

Table 1: Recognition performance in terms of CRPs of the proposed method, SVM and BPN.

Method	CRP %			
	10 degree	30 Degree	50 Degree	ALL (10, 30, 50)
SVM+KPCA (Proposed)	93.2	94	94.3	96.3
SVM	86.4	85.5	87.4	88.3
BPN	78	77.5	78.1	78.5

Table 2: Correct Recognition Percentage for different number of samples using proposed method, SVM and BPN.

Number of Samples	CRP%		
	SVM+KPCA	SVM	BPN
25	85.4	80	75
50	88.9	83.5	76.4
75	90.4	84.9	78.4
100	93.8	85.4	78.7
125	97.8	88.7	79.4

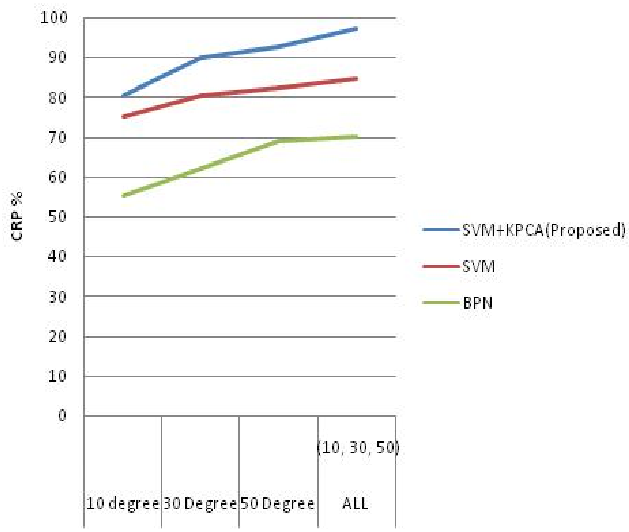

Fig.4 Recognition performance for the different training sets

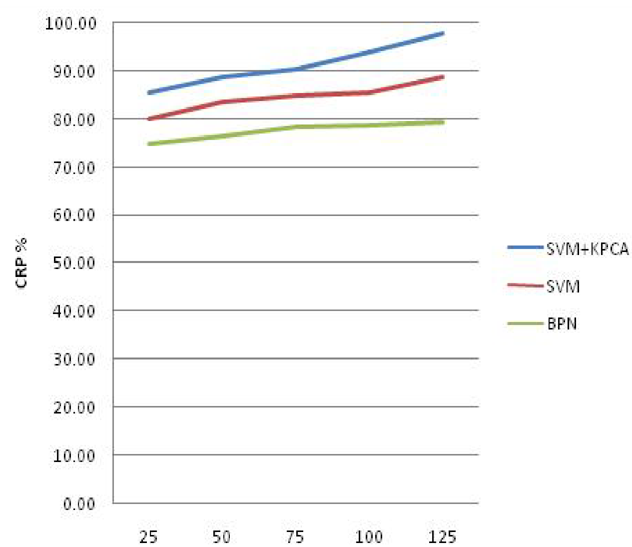

Fig.5. Correct recognition percentage for number of samples

6. Conclusion

This paper has presented SVM based object recognition using the Moment invariant Features. We have shown how the SVM recognizes the objects using the polynomial based kernel function. Also the KPCA is used for dimensionality reduction. For comparing the proposed method (SVM + KPCA) results, back-propagation method is implemented. Our proposed method is implemented in MATLAB with testing and training images available in the COIL-100 database. The SVM classifier performs well and provides high recognition rate compared to back-propagation network method.

References

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

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

[3] Daniel Madan Raja, S., and 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, 2011, pp. 1189 – 1195.

[4] Duda, and Hart, Pattern Classification and Scene Analysis, Wiley, New York, 1973.

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

[6] Haykin S, Neural Network: A Comprehensive Foundation, Prentice Hall, New Jersey, 1999.

[7] Jan Flusser, Tomas Suk, and Barbara Zitova, Moments and Moment Invariants in Pattern Recognition, John Wiley & Sons, Ltd., 2009, ISBN:978-0-470-69987-4.

[8] Krishna Singh, Indra Gupta, and Sangeeta Gupa. "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, 2010, pp. 67-78.

[9] Mi Hye Song, Jeon Lee, Sung Pil Cho, Kyoung Joung Lee, and Sun Kook Yoo, "Support Vector Machine Based Arrhythmia

Classification Using Reduced Features", International Journal of Control, Automation and Systems, vol-3, no-4, 2005, pp. 571 – 579.

[10] Muralidharan, R.; Chandrasekar, C. "Scale Invariant Feature Extraction for Indentifying an object in the image using Moment Invariants", Proceedings of IEEE International Conference on Communication and Computational Intelligence, 2010, pp.454 – 458.

[11] Narayanan Sundaram, Support Vector Machine Approximation using Kernel PCA, Technical Report, University of California, USA, 2009.

[12] Nene S.A, Nayar S.K, and Murase H, Columbia object image library (coil-100). Technical report, Colmubia University, 1996.

[13] Perantonis, S. J., and Lisboa,P.J.G, "Translation, rotation, and scale invariant pattern recognition by high-order neural networks and moment classifiers", IEEE Trans. Neural Networks, Vol-3, 1992, pp. 241–251.

[14] Rajasekaran, S., and Vijayalakshmi Pai, G.A. "Image recognition using Simplified Fuzzy ARTMAP augmented with a moment based feature extractor", International Journal of Pattern Recognition and Artifical Intelligence, Vol-14, No-8, 2000, pp. 1081-1095.

[15] Ronald A. Skoog, Thomas C. Banwell, Joel W. Gannett, Sarry F. Habbiby, Marcus Pang, Michael E, Rauch, and Paul Toliver. "Automatic Identification of Impairments Using Support Vector Machine Pattern Classification on Eye Diagrams", IEEE Photonics Technology Letters,Vol-18, No-22, 2006,pp. 2398 – 2400.

[16] Rui Pereira, and Luis Seabra Lopes, "Learning Visual Object Categories with Global Descriptors and Local Features", Proceedings of the 14th Portuguese Conference on Artificial Intelligence, Progress in Artificial Intelligence, Portugal. 2009, pp. 225 – 236.

[17] Shailedra Kumar Shrivastava, and Sanjay S. Gharde "Support Vector Machine for Handwritten Devanagari Numeral Recognition", International Journal of Computer Applications, Vol-7, No-11, 2010, pp. 9-14.

[18] Xiangjin Zeng, Xinhan Huang, and Min Wang. "Research of Invariant Moments and Improved Support Vector Machine in Micro-Targets Identification", Journal of Applied Science, Vol-8, No-21, 2008, pp. 3969-3974.

[19] 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, 2010, pp.47-54.

[20] Zhenchun Lei, Yingchun Yang, and Zhaohui Wu., "Ensemble of Support Vector Machine for Text-Independedt Speaker Recognition", International Journal of Computer Science and Network Security, Vol- 6, No-5A, 2006, pp. 163 – 167.

R.Muralidharan is a Ph.D student at Anna University of Technology, Coimbatore, India doing research in the field of Object Recognition Systems. He received M.Sc. Computer Science from Bharathidasan University in 2001 and M.Phil from Bharathiyar University in 2005. He is presently working as Assistant Professor in Computer Applications, KSR College of Engineering, Tiruchengode, Namakkal, India. He is a life member of ISTE and IACSIT. His research interests are in Image Processing, Object Recognitions and Neural Networks.

Dr.C.Chandrasekar received the B.Sc degree and M.C.A degree. He received his PhD from Periyar University, Salem at 2006. He worked as Head of the Department, Department Of Computer Applications at KSR College of Engineering from 2007. He has been working as Associate Professor in the Department of Computer Science at Periyar University, Salem. His research interest includes Mobile computing, Networks, Image processing, Pattern Recognition and Data mining. He is a senior member of ISTE, CSI. He was a Research guide at various universities in India. He has been published more than 50 technical papers at various National/ International Conference and Journals