Object Recognition using SVM-KNN based on Geometric Moment Invariant

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Abstract - **In this paper, a framework for recognizing an object from the given image is discussed. The proposed method is fusion of two popular methods in the literature, K-Nearest Neighbor (KNN) and Support Vector Machine (SVM). We propose the use of KNN to find closest neighbors to a query image and train a local SVM that preserves the distance function on the collection of neighbors. The proposed method is implemented in two steps. The first one concerns KNN to compute distances of the query to all training and pick the nearest K neighbors. The second step is to recognize the object using SVM classifier. For feature vector formation, Hu's Moment Invariant is computed to represent the image, which is invariant to translation, rotation and scaling. Experimental results are shown for COIL-100 database. Comparative analysis of proposed method with SVM and KNN is also given for each experiment.**

Keywords **– Support Vector Machine, Moment Invariant, K nearest neighbor, Object Recognition.**

I – INTRODUCTION

Recognizing objects from an image is difficult task in computer vision. Obviously human beings are recognizing objects through vision with great accuracy and apparently little effort, it is still unclear how this performance is achieved by the human being. When developing a computer-model to recognize an object, which rises to challenging theoretical problems such as how to model the visual appearance of the objects or to recognize the object. Pattern recognition is an important task in image analysis systems. In general the object recognition model is framed as image acquisition, preprocessing, feature extraction, and classification.

This paper describes an application of pattern recognition technique to the object recognition problem with favorable results using SVM-KNN and Moment Invariants. Ahmed et.al, states that the importance of the SIFT keypoints in object identification. J.Gao et.al, suggests the nearest neighbor is the best method for classifications of patterns. Luo Juan and Oubong Gwun suggests PCA-SIFT plays significant role in extracting the best features for image deformation. LiLi et.al, proves that the kNN is easier and simpler to build an automatic classifier. Dudani et.al, shows that moment invariants plays vital role in aircraft identification. Borji and Hamidi utilizes Support Vector Machine for recognition of Persian Font Recognition. Chun-Jung et.al., suggests Moment Invariants as feature for airport pavement distress image classification. Rajesekaran and Vijayalakshmi Pai proved the use of moment invariant as feature extractor for ARTMAP image classification. Krishna et.al., uses the support vector machine with the local features for classifying the leaf images. Xin-Han et.al., suggests that the support vector machine performs well in identifying micro parts. DanielRaja et.al., uses the moment invariants and Gray level co-variance matrix for the war scene classification. Ronald et.al., in his paper uses the support vector machine for automatic identification of impairments on eye diagram. From the literature survey made, the proposed method hybrids the KNN and SVM, to devise a new classifier that performs well.

The remainder of the paper is directed as follows. Section II describes the feature extraction process. Section III gives an overview of classification methods. Section IV presents our proposed method. Section 5 discusses these results. Finally, section 6 concludes the paper with a brief discussion of future research.

II – FEATURE EXTRACTION PROCESS

Feature extraction is considered as process of converting the given data into classifier acceptable format. In object recognition process, the image is to be represented into relevant features, so that the classifier is applied to recognize the object. In this paper, Hu's moment invariant is used as feature for the object recognition. The rest of this section deals with geometric moment invariants.

1) Geometric Moment Invariants

Geometric Invariant Moment is used in object recognition and pattern recognition applications. 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 approach using invariant features appears to be the most promising and has been used extensively since 1970. Its basic

$$\phi_1 = \eta_{20} + \eta_{02} \tag{3}$$

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

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

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

$$\begin{aligned}\phi_5 = &\left(\eta_{30} - 3\eta_{12}\right)\left(\eta_{30} + \eta_{12}\right)\left[\left(\eta_{30} + \eta_{12}\right)^2 - 3\left(\eta_{21} + \eta_{03}\right)^2\right] \\ &+ \left(3\eta_{21} - \eta_{03}\right)\left(\eta_{21} + \eta_{03}\right)\left[3\left(\eta_{30} + \eta_{12}\right)^2 - \left(\eta_{21} + \eta_{03}\right)^2\right]\end{aligned} \tag{7}$$

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

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

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 [10], 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

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

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. 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

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}}. \tag{2}$$

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

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.

III – Classification Method

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 [7]

$$\begin{aligned} y_i\left(w^T\varphi(x_i)+b\right) &\geq 1-\xi_i, \qquad \forall_i \\ \xi_i &\geq 0, \qquad \forall_i \end{aligned} \tag{10}$$

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

$$\phi(w,\xi_i)=\frac{1}{2}w^T w + C\sum_{i=1}^{N}\xi_i \tag{11}$$

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.

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

$$d(x,y)=\|x-y\|=\sqrt{(x-y)\cdot(x-y)}=\left(\sum_{i=1}^{m}(x_i-y_i)^2\right)^{1/2} \tag{12}$$

where x and y are points in R^m.

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 [10]. 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.

IV – Proposed Method – SVM-KNN

The proposed classifier 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 proposed method of SVM-KNN is given below, for a query (i.e., when an image is given as input to the proposed method),

1. Extract the feature (Moment Invariant) and construct the feature vector for the given image.
2. Compute the Euclidean Distance of the query to all training examples and pick the nearest K Neighbors.
3. If the K neighbors have all the same labels, the query is labeled and exit; otherwise, compute the pairwise distances between the K neighbors;
4. Convert the distance matrix to a kernel matrix using the “kernel trick” and apply SVM.
5. Use the resulting classifier to label the query.

In this paper, polynomial kernel function Eq.13 is used in the SVM procedure.

$$k(x_i, x_j)=\left(x_i^T x_j\right)^p, \tag{13}$$

where p = 1 gives standard PCA.

The proposed SVM-KNN 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 the feature vector is constructed. 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 single SVM and KNN. From the results, it is indicated that the proposed classifier is superior to some other classifier.

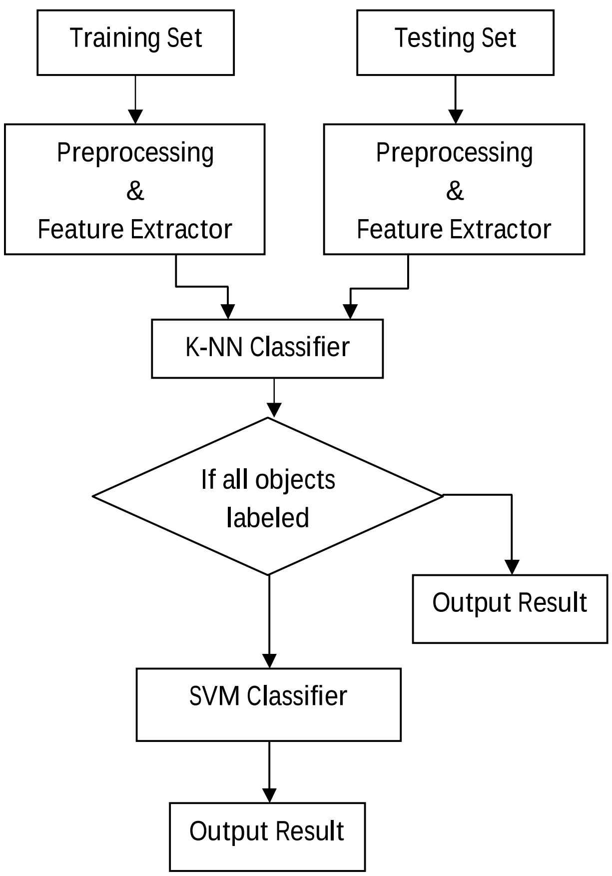

Fig.1. Proposed Model for Object Recognition.

V – Experimental Results

To experiment the proposed method, COIL-100 database is used, which is widely used in 3D object Recognition researches [12]. 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 proposed method was implemented in MATLAB 7.5 and with images of coil-100 database. 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 arranged in such a way to construct the feature vector.

The KNN classification algorithm tries to find the K nearest neighbors of x_0 and uses a majority vote to determine the class label of x_0, where x_0 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. Some of the images chosen for training and testing are given in fig.2. Table I and fig.3 shows the performance of the proposed method compared with the traditional SVM and KNN method.

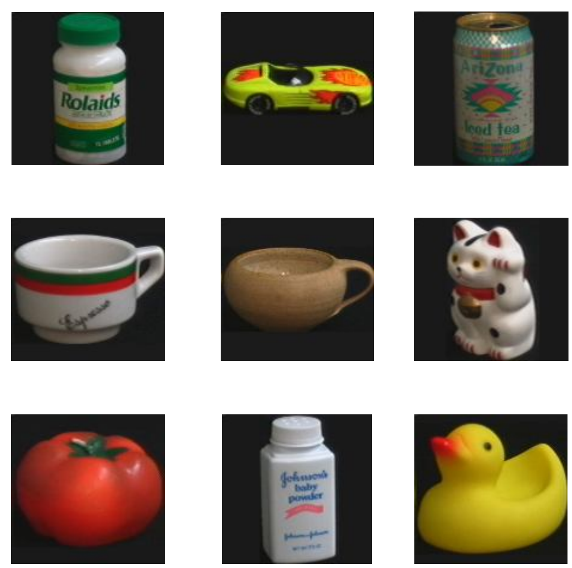

Fig. 2. Some examples of objects from COIL-100 database

TABLE I. RESULTS OF THE CLASSIFIER WITH DIFFERENT NO. OF TRAINING SETS

No. of Training images	**% of recognition (based on Positive recognition)**			
	50	**100**	**150**	**200**
SVM + KNN	85%	90%	93%	95%

SVM	80%	81.3%	84.2%	87.4%
KNN	75%	78.5%	79%	82%

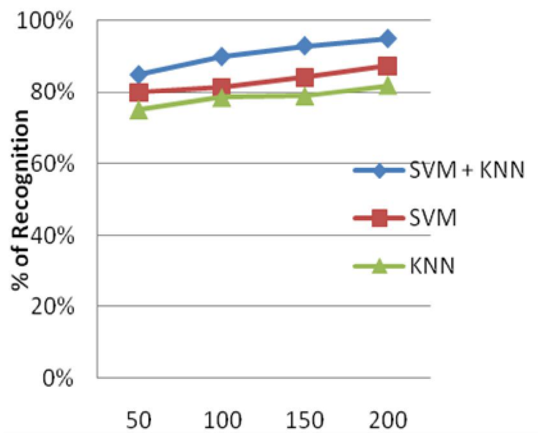

Fig.3.performance of the proposed method for different number of training images.

From the above graph fig.3 the proposed method outperforms the single SVM and KNN. The proposed method is performed with less amount of memory and takes less computation time compared with single SVM.

VI – Conclusion

From experimental results in the table.I, it is clear that combining SVM and KNN with moment invariant feature can produce better results. Most of the results are even better than the traditional methods like KNN and SVM. The proposed method uses polynomial function as kernel function. Future work will include the process of Kernel principal component analysis to reduce the feature vector so that high-dimensional data can be handled with less complexity. More work need to be performed to increase the recognition percentage.

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