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Face Recognition based on Histogram of Oriented Gradients, Local Binary Pattern and SVM/HMM Classifiers

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Abstract

Face recognition is one of the challenging biometric technologies which has widespread applications in many fields such as access to security systems, identification of a person in law enforcement, identifying the culprit during riots, breach of security etc. In many of the face recognition techniques, the unique features of the face image are extracted and compared with the images of the database to produce better success rates. In this paper we take into account both shape and texture information to derive feature vector based on Histogram of Oriented Gradients (HOG) and Local Binary Pattern. In both algorithms, the face is divided into small regions and features are extracted. The performance of different algorithms with Support Vector Machine (SVM) and Hidden Markov Model (HMM) classifier are compared. It is found that the concatenation of feature vector derived from HOG and LBP with SVM as classifier has produced better result of 99.4% of recognition rate.

Keywords: Histogram of Orient Gradients, bin, Local Binary Pattern, Support Vector Machine, Hidden Markov Model; ORL data base.

Introduction

During the last few years, face recognition has received significant attention in the field of application of image analysis and understanding. There are two reasons for this trend; the first is the wide range of commercial and law enforcement applications, crowd surveillance, access control, content based image database management, criminal identification and so on and the second is the availability of feasible technologies after 30 years of research. In recent days, the face recognition techniques are adopted in accessing the devices such as laptop, mobiles, internet access so that the portable devices could not be stolen. In the modern technological world, it is widely being used in face taggers on desktops while taking up online examinations related to government jobs, entrance to IITs, medical colleges etc. so that the impersonation is avoided.

The face recognition tasks are categorized as face identification and face verification. Face identification is the technique to identify a person among the given set of gallery face sets. Face verification is to verify whether the face belongs to the same person or not. In most of the surveillance based applications, the face images may not be taken at highly illuminated and frontal pose images, and then there is a need to develop algorithms which perform well with unconstrained face images. Face recognition has the benefit of being a passive, non intrusive system for verifying personal identity.

Contribution: In this paper, textural Features such as Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP) are computed from the preprocessed facial images. The HMM/SVM classifiers are used for face recognition using ORL face database.

Organization: The paper is organized into the following sections. Section 2 is an overview of related work, the model is described in Section 3, HMM/SVM classifiers are discussed in Section 4, Section 5 is results and Discussions and Conclusion are contained in Section 6.

Literature survey

Zhifeng Li, et al.,(1) proposed a discriminative model to address face matching in the presence of age variation by representing each face by designing a densely sampled local feature description scheme, in which scale invariant feature transform (SIFT) and multi-scale local binary patterns (MLBP) serve as the local descriptors. By densely sampling the two kinds of local descriptors from the entire facial image, sufficient discriminatory information,

including the distribution of the edge direction in the face image (that is expected to be age invariant) can be extracted for further analysis. Since both SIFT-based local features and MLBP-based local features span a high-dimensional feature space, to avoid the over fitting problem, an algorithm has been developed, called multi-feature discriminant analysis (MFDA) to process these two local feature spaces in a unified framework. The MFDA is an extension and improvement of the LDA using multiple features combined with two different random sampling methods in feature and sample space. By random sampling the training set as well as the feature space, multiple LDA-based classifiers are constructed and then combined to generate a robust decision via a fusion rule. Younghwan Kim et al., (2) presented a motion and similarity-based fake detection algorithm for biometric face recognition systems. First, an input video is segmented into foreground and background regions. Second, the similarity is measured between a background region, i.e., a region without a face and upper body, and an original background region recorded at an initializing stage. Third, a background motion index is calculated to indicate the amount of motion in the background region compared with the motion in the foreground region. By combining the result of similarity and the result of the background motion index, a fake video can be detected robustly with a regular USB camera. Shekar, B.H.et al.,(3) suggested a robust and an accurate face recognition model which uses the feature extraction capabilities of fractional discrete cosine transform (FDCT). FDCT on the face image database is applied and use transform coefficients as features. The proposed model is tested on publicly available standard AT&T face database to demonstrate the recognition accuracy.

Wen-Sheng Chen et al., (4) proposed a novel regularized LPP (RLPP) approach using supervised graph and regularization technique. Dimensionality reduction technologies are very important for pattern representation and recognition. Among them, locality preserving projection (LPP) is a manifold dimensionality reduction scheme and has been successfully applied to face recognition. As LPP is an unsupervised linear approach, its performance will degrade for classification tasks; especially, when the dimension of input space is greater than the number of training data, singularity problem will occur and LPP cannot be implemented directly. To tackle the draw backs of LPP algorithm the proposed RLPP method has been tested and evaluated with two public available databases, namely ORL and FERET databases. Ito, K.et al., (5) presented a 2D face recognition algorithm using phase-based

correspondence matching. The phase information obtained from 2D DFT (Discrete Fourier Transform) of images contains important information of image representation. The phase-based image matching is successfully applied to sub-pixel image registration tasks for computer vision applications and image recognition tasks for biometric authentication applications. Hierarchical block matching using phase information, i.e., phase-based correspondence matching, can find the corresponding points on the input image from the reference points on the registered image with sub-pixel accuracy. For face recognition, the phase-based correspondence matching is useful for minute change of texture, such as facial expression change, illumination change, etc.

Wei He et al., (6) dealt Small Sample Size (3S) problem of Locality Preserving Projection (LPP) approach in face recognition. It is well-known that the dimension of pattern vector obtained by vectorizing a facial image is very high and usually greater than the number of training samples. Under this situation, 3S problem always occurs and direct utilizing LPP algorithm is infeasible. To deal with this limitation, a novel subspace discriminated LPP approach (SDLPP) is proposed based on modified LPP criterion and supervised graph. Furthermore, our SDLPP approach has low computational complexity. Two face databases, namely ORL and FERET databases are selected for evaluations. Jiwen Lu et al., (7) proposed a multi linear locality preserving canonical correlation analysis (MLPCCA) method for face recognition. Motivated by the fact that both spatial structure information within each face sample and local geometry information among multiple face samples are useful for facial image feature extraction, they are utilized simultaneously and derive an improved canonical correlation analysis algorithm - MLPCCA - to seek multiple sets of pair wise projection bases to maximize the correlation of two facial image sets. The proposed MLPCCA method is designed to characterize the potential nonlinear correlation of two image sets by utilizing both the spatial and local geometrical information hence is more suitable for face recognition across large pose and illumination variants.

Bozorgtabar, B et al.,(8) proposed Genetic Programming GP to face recognition. First Principal Component Analysis (PCA) is used to extract features, and then GP is used to classify image groups. To further improve the results, a leveraging method is also utilized. It is shown that although GP might not be efficient in its isolated form, a leveraged GP can offer results comparable to other Face recognition solutions. Rajkumar, N et al.,(9) presented a new face

recognition method based on 2D Level 2 Wavelet decomposition in, PCA (principal Component Analysis) with singular value decomposition, and Bayesian Classifier is proposed. This method consists of three steps: i) Preprocessing, ii) feature extraction using curvelet, PCA with Singular value decomposition iii) classification and recognition using Bayes' algorithm. Combination of PCA, with Singular Value Decomposition and Bayesian classifier is used for improving the rate of recognition when a few samples of images are available. Bayesian classifier is used to reduce the number of any misclassification caused by non-linearly separable classes. This type of recognition can play an important role for authentication purpose in security related areas such as airport, banking, and secret mission. Baboli, A.A.S et al.,(10) proposed a method to find the best dimension for Multilinear discriminant analysis (MDA). The main algorithm is the same as MDA. As we knew, MDA is using an iterative algorithm to maximize a tensor-based discriminant criterion. Because the number of possible subspace dimensions for any kind of tensor objects is extremely high, so testing all of them for finding the best one is not feasible. So this paper is presented a method to solve that problem. The main criterion of this algorithm is not similar to Sequential mode truncation (SMT) and full projection is used to initialize the iterative solution and find the best dimension for MDA. The suggested method saves the extra times that will be spent to find the best dimension and therefore the execution time decreases.Jiangwei Li et al., (11) proposed a feature descriptor, Local Primitive Code (LPC), which exhibits impressively discriminative capability on various face datasets. Essentially, LPC descriptors are somewhat like filter banks of Gaussian derivatives to capture multi-scale and multi-orientation image local textures but meanwhile enables faster feature extraction. It employs a framework composed of two stages: Firstly facial images are preprocessed by the pool of differential and quotient filters to generate numerous filtered images with various textures, and then directional binary encoding (DBE) operates on filtered images for primitive code mining. With such stages, feature maps with complementary discriminative information will be generated, and the fusion of them improves face recognition performance. Yanqi Tan et al.,(12) presented Contourlet-Based Feature Extraction with LPP for Face Recognition by introducing the application of contourlet transform in conjunction with Locality preserving projection (LPP) which is a successful method in face recognition for feature extraction. However, the recognition efficiency of LPP technique
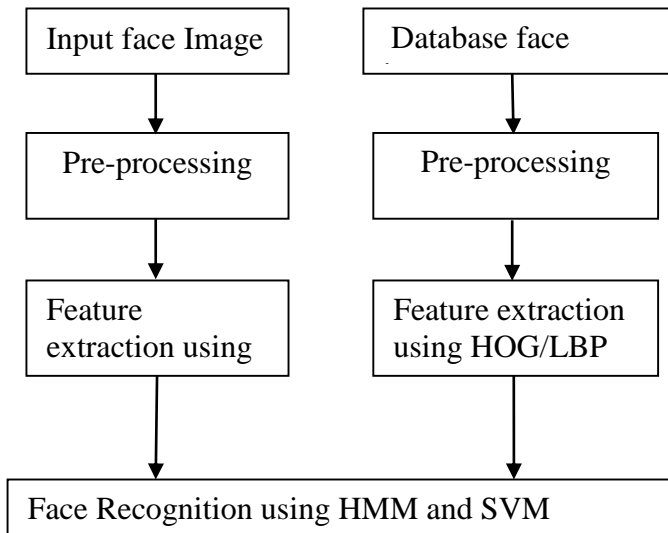
is often degraded by the very high dimensional nature of the image space. The difficulty to calculate the bases to represent the original facial images is being overcome using the algorithm describing image in vector form and is often applied in data after dimension reduction by PCA which result in the algorithm sensitive to how to estimate the intrinsic dimensionality of the nonlinear face manifold in the PCA preprocessing step. Baozhu Wang et al.,(13) proposed an efficient feature extraction method based on the discrete contourlet transform using fast independent component analysis (Fast ICA) and the angle similarity coefficient(cosine) as the distance measure is proposed. Firstly, each face is decomposed using the contourlet transform. The contourlet coefficients of low and high frequency in different scales and various angles are obtained. The frequency coefficients are used as a feature vector for further processing. Secondly, considering the specificity of face images, the Fast ICA algorithm based on negentropy to extract the face feature information is adopted and according to the distance, face feature is classified.

Eunsoo Choi et al.,(14) presented a novel face recognition algorithm inspired by information taken from human fixation patterns. Augmentation of a LGBP (Local Gabor Binary Pattern) algorithm - a well-known face recognition algorithm - to allocate different weights to each facial part during processing. For deriving the weights, data is analyzed from a human face recognition experiment using eye-tracking. Eye-tracking allows determining the facial parts during the recognition process which represent salient regions for human processing. Face images are pre-processed during the recognition step using a weight mask based on the salient regions from the eye-tracking data. A comparison with the standard non-weighted LGBP approach demonstrates the efficacy of this method with the weighted method performing better under lighting changes.

Nutao Tan et al.,(15) proposed a new algorithm of face recognition that is based on a single face image. The new algorithm can be divided into three steps: first, we compute horizontal and vertical edge images from the gray image; then, local binary pattern histogram is extracted from those two edge images; finally, elastic matching is used to classification. Experimental result on some standard face databases show that proposed method can substantially improve the recognition performance and is robustness to pose, illumination and expression.

Model

The model of Face Recognition based on LBP and HOG using SVM/HMM Classifiers is shown in the Fig 1. In the first stage the test facial image and data base images are preprocessed to reduce noise. The HMM/SVM classifiers are used face recognition using ORL face database.

Input face Image	Database face
Pre-processing	Pre-processing
Feature extraction using	Feature extraction using HOG/LBP

Face Recognition using HMM and SVM

Fig 1. Model of Face Recognition based on HOG/LBP using Classifiers

In the next stage textural Features such as Local Binary Pattern (LBP) and Histogram of Oriented Gradients (HOG) are computed from the preprocessed facial images..

ORL Database: There are ten different images of 40 distinct persons. It consists of images of some persons taken at different times of the day. Thus it contains variations in facial expressions with open/closed eyes, smiling/non smiling faces, and different facial expressions with or without glasses. All the images were taken against a dark homogeneous background with the subjects in an upright, parallel position, with tolerance for some tilting and rotation of up to about 20 degrees. The images are grayscale with a resolution of 92 X 112.

3.1 Histogram of Oriented Gradients (HOG):
We follow the procedure in [16] for to extract the HOG feature, trilinear interpolation and Guassian Weighing are two important sub-procedures in HOG construction.

Initially the face image is divided into small connected regions called cells and the histogram of edge orientation is computed for each one over the pixels of the cell using discrete derivative masks like Sobel masks. Each pixel in the cell will be a parameter for edge orientation and the gradient element is attached to it, thus the computation is performed for orientation

bins. Normally histogram channels are spread over 0^0-180^0 degrees or 0^0-360^0 degrees depending on whether the gradient is signed or unsigned.

Histogram counts are normalized by accumulating a measure of local histogram energy over the connected regions. These results are used to normalize all the cells in the block and the HOG description is created. The HOG descriptor is made invariant to scaling and rotation. The following steps are used:
1. Scale space extreme detection
2. Orientation assignment-here dominant gradient orientation is detected
3. Descriptor extraction
Fig 2 shows an example patch with their corresponding HOG
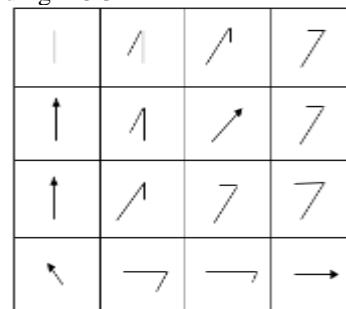
Fig 2. HOG descriptor. Each Cell shows the orientation of the descriptor

After HOG descriptor of each image is defined, the cluster process is applied to obtain clusters of different regions like mouth, nose, eye, lips etc. to get histogram based on the frequency of appearances in the image. The concatenated histogram entries of the cells from the HOG feature vector. The overview of construction HOG feature vector is as shown in Fig 3.
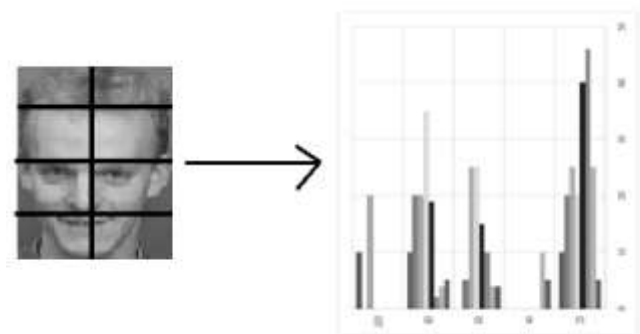
Fig 3. Overview of final feature vector construction using HOG descriptor

3.2 Local Binary Pattern (LBP):
LBP operator is one of the best feature descriptor for face recognition since the face is a composition of micro patterns which can be well described by the LBP operator. The LBP operator assigns a label to every pixel of an image as shown in Fig 4 by thresholding

the   3 X 3 neighborhood of each pixel with the center pixel values and the code for the center pixel produced by concatenating the eight cells to 8 bit code.
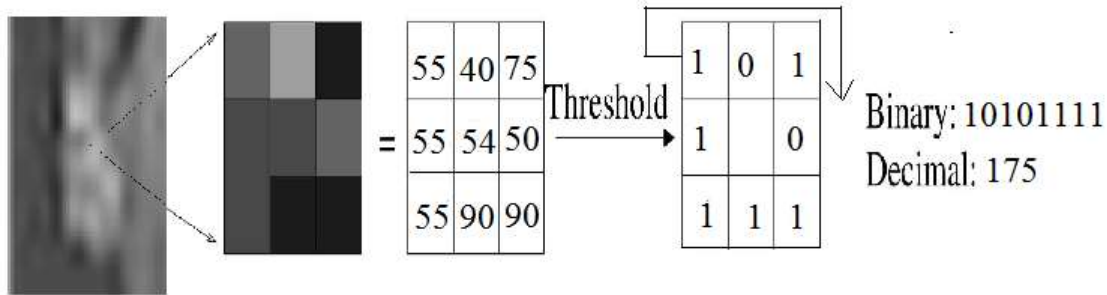

Fig 4, The basics of LBP operator

Later the LBP operator was extended to use neighborhood of different images as shown in   Fig 5. Thus a circle is made with a radius R from the center pixel and neighborhood size of P equal spaces pixels on the circle gives the operator LBP $_{(P,R)}$. For example in Fig 5, LBP $_{(8,1)}$ uses only 8 pixels on the circle with a radius of 1 pixel from the center as shown in Fig 5. Similarly, LBP $_{(16,4)}$ uses only 16 pixels on the circle with a radius of 4 pixels from the centre. Here the bilinear interpolation is used. In our project, the facial image is divided into 7 X 7 matrixes so as to get 49 blocks as shown in Fig 6. In our paper, the LBP pattern introduced by Ojala et al [17] is used.
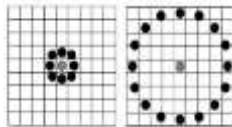
P=8, R=1 P=16, R=4
Fig 5. Circular neighbor sets for different values of P and R

Fig 6. An image divided into 7X7 matrix

Uniform Local Binary Patterns (LBP):
A uniform LBP is the defined as uniform if it possesses maximum two transitions 0-1 or 1-0 when bits pattern is generated. Therefore the 8 bit string 01100000, 00000000, 11100001 are termed as uniform. In the face data set, it is seen that 92% of the pattern accounts for uniform LBP(17). Thus little information is lost by assigning all non uniform patterns to a single number. Bin histograms of the labels computed over an image are used as Texture descriptors. Each bin of histogram (LBP code) is also called as "micro text on" with

$LBP^{u2}_{p,R}$, there can be P (P-1) +2 patterns are possible. Some of the local primitives as shown in Fig 7 are spots, line ends, edges and corners.

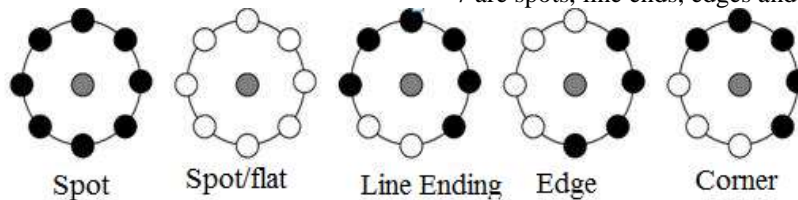Spot   Spot/flat   Line Ending   Edge   Corner
Fig 7. Different Texture primitives of LBP

Feature vectors
Once the LBP for every pixel is computed, the feature vector is constructed [18] if the face has K square regions for example, in the Fig 6, the face is divided into 7 X 7=7^2 =49 regions. For every region, a histogram is constructed. Thus to get the information of the faces, the image is divided into M small non overlapping regions R_0, R_1,....R_M as shown in Fig 8.
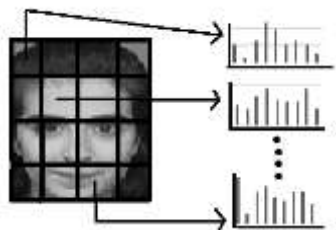
Fig 8. Face image with histogram for every small region.

The feature vector is constructed by concatenating the LBP histogram into a big histogram. The feature histogram is defined as

$$\sum_{x,y} I(f_i(x,y) - i)I(x,y) \in R_j$$

Where $i = 0, 1 \ldots L-1$ and $j = 0, 1 \ldots M-1$

Training Module: The training models i.e, the Hidden Markov Model and SVM Classifier are discussed as follows

Hidden Markov Model
An HMM is a stochastic model used to device and design sequential data represented by a sequence of observations. HMM is defined as "a doubly embedded stochastic process with an underlying process that is not observable (it can be stated as hidden), but can only be visualized through another set of stochastic processes that produce the sequence of observations" [19]. A standard HMM has the following parameters :

N = number of states;
M = number of distinct observation symbols;
$V = [v_1, v_2, ..., v_M]$ - set of individual observation symbols;
Individual states are labeled as {1, 2... N}
$Q = [q_1, q_2, q_3, ..., q_T]$ Where q_t denotes the state at time t ;
The initial state distribution $\pi = \{\pi_i\}$

$$\pi_i = P[q_1 = i] \quad 1 \le i \le N$$

(1)
$O = [o_1, o_2, ... o_T]$; $O_i \in V$, $\forall i$;
T = length of the observation sequence;
t = clock time; $t \in (1, 2, 3, ..., T)$;
The state transition probability $\mathbf{A} = \{a_{ij}\}$ where

$$a_{ij} = P[q_{t+1} = j \mid q_t = i] \quad 1 \le i, j \le N$$

(2)

$\mathbf{B} = \{\mathbf{b_j(o_t)}\}$ Observation probabilities $b_j(k)$ of observing symbol v_k while being in state q_j. HMM parameters are often referred to as $\lambda = (\pi, A, B)$. After a series of observations and with the above parameters we can calculate the probability of the observation sequence.

(1) Forward Variable:
Consider the forward variable [19] $\alpha_t(i)$ defined as
$$\alpha_t(i) = P(o_1 o_2 ... o_t, q_t = i \mid \lambda)$$

(3)
Equation (3) represents the probability of the partial observation sequence, $o_1 o_2 .... o_t$, (until time t) and state i at time t, given the model λ.

(2) Backward Variable:
Similarly the backward variable [19] $\beta_t(i)$ defined as

$$\beta_t(i) = P(o_{t+1}, o_{t+2} ... o_T \mid q_t = i, \lambda)$$

(4)
Equation (4) defines the probability of the partial observation sequences from $t+1$ to the end and given state i at time t and the model λ.

P $(O \mid \lambda)$ is the probability of the observation sequence given the model λ. It can be computed using the forward variable as follows [19]:

$$P(O \mid \lambda) = \sum_{i=1}^{N} \alpha_T(i)$$

(5)
The Baum-Welch re-estimation procedure is employed during the training phase for parameter re-estimation of model λ.

Recognition phase:
Left-Right Banded Structure (LRB) HMM model is devised and trained for each of the face class available in the database. N HMM models will be created and trained for a total of N facial classes. For the purpose of face recognition the feature vector is modeled for the test image and used as observation sequences. The HMM model which corresponds to the maximum probability score is then identified as the recognized facial class for the given test face.
To order to verify the test image, a threshold is computed for each facial class. For the unknown test image of the face, maximum probability score exceeds the above threshold value, and then the unknown test facial image is identified as a recognized face. However if the unknown facial image's maximum probability score is lower than the threshold value, then the unknown facial image is rejected.
The threshold is computed as follows:
1) The probability scores of all the samples corresponding to the facial class under consideration are recorded. The mean μ_1, and

standard deviation, σ_1, of the distribution is computed from the scores.

2) For each facial class, compute the threshold as :

$$T = \frac{\mu_1 \sigma_2 + \mu_2 \sigma_1}{\sigma_1 + \sigma_2}$$

(6)

Support Vector Machine Classifier

Support Vector Machines (SVM) is used to analyze data and recognize patterns. They consist of a set of supervised learning models incorporated with learning algorithms. Normally for classification and regression analysis SVM are employed. SVM are used to solve multi class problems. An SVM model as suggested by Vapnik et al [20, 21] is a representation of the examples as points in space and assigns the new examples into one category or other. The aim of the algorithm is to find hyper plane between two classes. Two parallel hyper planes are constructed on each side of the hyper plane that separate the data. The separating hyper plane as shown in Fig 9 is the hyper plane that maximizes the distance between the two parallel hyper planes. Classification between two classes i.e. Class A and Class B is shown in Fig 9.

If the hyper plane has the largest distance to the nearest training data point of any class then it is assumed that a good separation is achieved. But in general, the larger the margin or difference between these parallel hyper planes, then the generalization error of the Classifier [21] will be better.

If the training data of N data is given by:
$\left\{ x_n / n = 1, N \right\}$ then the linear support Vector Machine classifier is defined as shown in Equation (7)

$$f(x) = \sum j\, a_j\, x_j \cdot x + b$$

(7)

When $\{x_j\}$ set of Support Vectors and the parameters aj and b are are determined by solving the quadratic problem given in [21].
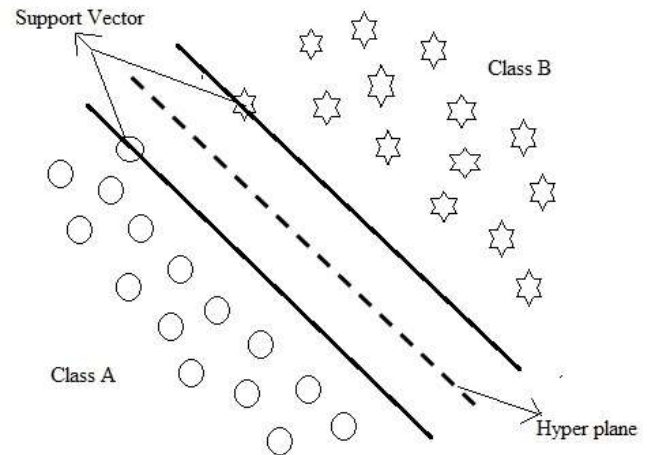

Fig.9 shows classification by SVM between two classes

Results and discussions

In this paper the result is evaluated using SVM, HMM and Chi Square statistical methods. The features of the facial images are extracted using texture features such as Histogram of Oriented Gradients and Local Binary Pattern. It is based on dividing a facial image into small grids and the descriptor for each grid is computed. The ORL data base having 10 different facial images of 40 persons were considered. In this work a random selection of 5 facial images per persons were selected for training and remaining were used for testing. The selection of suitable function for SVM is based on trial-and-error basis. . The recognition rate for Chi Square Distance method, SVM and HMM classifiers with different descriptors are shown in the Table.1.

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Table 1. Comparison of Performance of different classifiers on ORL data base

Feature extraction method	Classifier	%Recognition Rate
HOG	Chi Square	98.1%
LBP	Chi Square	98.90%
HOG + LBP	Chi Square	99.32%
HOG	SVM	98.20%
LBP	SVM	99.30%
HOG + LBP	SVM	99.40%
HOG	HMM	98.20%
LBP	HMM	98.40%
HOG + LBP	HMM	99.23%

It is seen that the results with combined feature vector consisting of features extracted from HOG and LBP descriptors using SVM classifiers gives a better recognition rate of 99.40%.

Conclusions

In the modern technological world, face recognition has become a very interesting and active topic in computer vision research. It is very important to design an efficient descriptor to produce better results. In this research paper, an effort is made to extract texture features of the face using Histogram of oriented Gradients and Local Binary Pattern. The feature vectors of test and data base images are compared using Chi Square distance method, SVM and HMM classifiers. It is found that combined feature vector consisting of features extracted from HOG and LBP descriptors using SVM classifiers gives a better recognition rate of 99.40%. Different grid dimensions with different descriptors may be computed to get better performance.

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