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An Active Appearance Model based Face Recognition from Surveillance Video

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Abstract:
For the past few years, the Face Recognition (FR) is becoming active research area in the field of Face Identification and verification. The Deep convolutional neural networks (CNNs) are extensively becoming popular in the field of FR in recent years but works with labelled datasets containing very large number of training samples. It is also difficult task to collect large number of Face images for training the model. Decision tree (DT) and-Nearest Neighbour (K-NN) performs better when the training set is small and computationally expensive when the training samples increases. In order to overcome the problem of low recognition and high computation complexity of Face Recognition (FR) space, this research paper proposes a Support Vector Machine (SVM) based FR to recognize the faces from video frames and still images. During the SVM training, the parameters are optimized with particle swarm optimization (PSO) technique , which enhances the FR rate. In this method initially, the noise is eliminated from the probe image using Adaptive median Filter (AMF) and then the feature vector is generated using the combination of Active Appearance Model(AAM) and the shape model. The recognition performance is analyzed on UPC Video Database, YouTube Face Database(YTF),ORL database and Yale B face sets . The main application of this research is to identify Faces from Poor quality surveillance video as well as still images.

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I. INTRODUCTION

Human identification using Face biometric can be a method of confirming one or more individuals particularly from still or video images using a stored database [1] [2] [3]. Face Recognition (FR) finds a number of applications in human-computer interactions, authentication and verification and security surveillance [4]. FR is broadly classified into two categories, feature-based methods and appearance-based methods [5]. The Human facial parts are considered as very significant geometrical constraints and are acceptably used in feature-based methods. For example, elastic bunch graph matching is a well-known face recognition method comes under feature based method [6] while active appearance model [7], based on appearance-based method. In appearance based methods the intensity or intensity-derived parameters are utilized for recognition [1] [8].

The primary two stages of a face recognition technique are face detection and face identification [4][9][10]. Initially in the face detection phase, the presence of face image(s) in a given input image/video is located. Then it is used to recognize the person from the database of the registered individuals, shows the reasonable significance of having both face detection and face recognition methods[9][11][12]. The important characteristics in face recognition are the variations in illumination, pose, identity [10], facial expression, aging, hair style, make-up, scale etc. The variation in pose and illumination are real challenging problems because the same person may appear extremely different in two different images with these abnormalities [11][13].

As a solution, to overcome the problem and to manage pose variations in face recognition view-based method is principally used. In this method, the images are captured from diverse view angles to recognize the face images of the persons [12] [13]. The Video based FR algorithms that consistently use both spatial and temporal information for face recognition has began extensively popular recently, but still requires more attention [13][15]. A typical face recognition system identifies the face regions automatically from video frame/ still image and extracts the distinguishing facial identities, which is often a difficult task [16].

II. LITERATURE SURVEY

A few research works that are related to our video face recognition system are reviewed in the following section.

Wei Hu et al.,[17] proposed a model called SeqFace, for learning the discriminative feature using Deep Neural Network. The FR performance is greatly increased recent years using Deep learning methods. Plenty of datasets are also available to train these Deep learning networks. To achieve state-of-the-art performance on Face Recognition , high quality datasets are very essential but expensive to collect. SeqFace also offers a Face dataset which includes a large number of face sequences collected from videos. In order to enhance the discrimination power of deep face features , a new proposed discriminative sequence agent (DSA) loss and label smoothing regularization (LSR) and are employed using the sequence data. This method is also tested on Labeled Faces in the Wild (LFW) and YouTube Faces (YTF), with a single ResNet and achieved an accuracy of 98.12% and 99.03% respectively.

Jiankang Deng et al.,[18] proposed a model called ArcFace, which offers a highly discriminative feature for Face Recognition. The Deep learning method has become extensively popular because of its power to discriminate among classes using loss functions. Several loss functions are already exists but still some discriminatory problem persists. Centre loss is one such loss function to achieve intra-class compactness ,the function identify and penalises the distance between the features and their corresponding class centers in Euclidian space. SphereFace is another loss function, which penalises the angles between the deep features and their corresponding weights .The SphereFace assumes the linear transformation matrix of the last fully connected layes of the Deep Convolutional Neural Network as class centers. A good loss function always maximizes the inter class variance and minimizes the intra-class variances. This model proposes a Additive Angular Margin Loss function and this proposed model has a clear geometric interpretation due to the exact correspondence to the geodesic distance on the hyper sphere. This algorithm achieved an accuracy of 98.02% on YTF Database and 99.83% on LFW database.

Hoa wang et al.,[19] Proposed a model ,CosFace by introducing a new loss function, large margin cosine loss (LMCL). The loss functions are the key idea for the success of CNN because of its capability to discriminate the features. The idea behind all loss function are to maximize interclass variance and minimize the intra class variance. Already several loss functions such as centre loss, large margin softmax loss, and angular softmax loss are used in CNN training still exists some drawbacks. The LMCL is hence proposed , to overcome the draw backs of center loss, large margin softmax loss, and angular softmax loss . Here the softmax loss is formulated as a cosine loss by using L2 norms for both features and weight vectors which successfully removes the radial variations, hence increases inter class variance , reduces the intra-class variance and maximizes the decision margin in the angular space. As a result, minimum intra-class variance and maximum inter-class variance are achieved by virtue of normalization and cosine decision margin.This

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cosine decision margin maximization concept is implemented successfully and demonstrated successfully using YTF and LWF databases. This algorithm achieved an accuracy of 97.6% on YTF Database and 99.73% on LFW database

Yu Liu et al., [20] proposed set to set image recognition. In this method they introduced learning metric to assure the quality of the images in the image sets. The quality aware network (QAN) is proposed to learn the quality of each image in the set. The network initially extracts the appearance feature and predicts quality score of each sample in the set. The final feature embedding is obtained by aggregating the both the quality score and feature embedding. This feature embedding obtained is used in face verification and identification. The result show a maximum accuracy of 96.17% in YTF faces.

Xiang Wu et al, [21] proposes a variation of maxout activation function ,called Max-Feature-Map (MFM) is introduced in each of the Convolution layers of CNN . MFM uses a competitive relationship to approximate an arbitrary convex activation function rather than using many feature maps to linearly approximate the activation function as in the case of maxout. MFM is not only selects features from the feature maps but also separates noise from the informative signals.MFM has shown its efficiency while selecting the features between two feature maps. Next, they designed three networks reducing the number of parameters to get better performance and computational costs. Finally, a semantic bootstrapping method is applied to enhance the prediction capability of the networks effectively on noisy labels. Experimental results show that the proposed framework effectively utilizes the large scale noisy data for training the network. The proposed work is efficient both with computational costs and storage spaces. This algorithm achieved an accuracy of 95.54% on YTF Database and 99.33% on LFW database

III. FACE RECOGNITION WITH AAM, SVM AND PSO

The proposed face recognition method develops a technique to recognize the face images from the input video sequences. The proposed face recognition process is achieved by the PSO with SVM techniques. The proposed system mainly comprised of four stages namely, (i) Preprocessing by AMF (ii) Feature Extraction using AAM (iii) Support Vector Machine (SVM) and (iv) Optimization of SVM by PSO. These four stages are consecutively performed and the video faces are recognized more effectively. The Structure of our proposed video face recognition system is illustrated in Figure 1.

3.1 Pre-processing by AMF

In video face recognition, first we carry out the pre-processing process on the given input video frames. Here we have to exploit an adaptive median filtering (AMF) to remove the noise from the video frames. Let us consider the given set of training and testing images,

$$\begin{aligned}&D_i^{tr}(a,b), D_j^{te}(a,b); a=0,1,\cdots A-1, b=0,1,\cdots B-1\\&and\ \ i=1,2,\cdots M,\ j=1,2,\cdots N\end{aligned} \tag{1}$$

In Equ. (1), $D_i^{tr}(a,b)\, and\, D_j^{te}(a,b)$ represents training and testing images with the size of $A \times B$, whereas i, j is the number of training and testing images. These numbers of training and testing images are given to the adaptive median filtering technique for pre-processing and these pre-processed video frames are given to feature extraction. The pre-processed images from the adaptive median filtering are represented as $D_i^{tr}(a,b)'\, and\, D_j^{te}(a,b)'$.

3.2 Feature Extraction using AAM

In feature extraction stage, the AAM features are extracted from the given pre-processed images $D_i^{tr}(a,b)'$. In AAM, the active portions are manually labelled to extract the shape model parameters and appearance model parameters. Based on the placed x and y coordinates values two vectors are generated namely, X_{ik} and Y_{ik} $: k=1,2,\cdots,A_p$, where A_p is the active portion of an image.

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The grey portions of I_i are extracted using the X_i and Y_i as follows

$$G_{ik} = \begin{cases} g_i(x,y) \ ; if \ x \le X_{ik}(l) \ and \ y \le Y_{ik}(l) \ ; l = 1,2,\cdots A_p \\ 0; \quad otherwise \end{cases}$$

(2)

$$g_i(x,y) = 0.3 I_i^R(x,y) + 0.6 I_i^G(x,y) + 0.1 I_i^B(x,y) \tag{3}$$

In Equ. (3) $I_i^R(x,y), I_i^G(x,y) \, and \, I_i^B(x,y)$ are the red, green, blue values of the training image $I_i(x,y)$. Afterward, the normalization is applied over the X, Y and G to get the shape and grey parameters. The process of normalization over the X, Y and G as given as,

$$\overline{X_k} = \frac{1}{M}\sum_{i=0}^{M-1} X_{ik} \tag{4}$$

$$\overline{Y_k} = \frac{1}{M}\sum_{i=0}^{M-1} Y_{ik} \tag{5}$$

$$\overline{G_k} = \frac{1}{M}\sum_{i=0}^{M-1} G_{ik} \tag{6}$$

, By using X,Y and G values the shape and gray parameters are computed as follows

$$S_p^{(ik)} = \begin{bmatrix} (\overline{X}_k - X_{ik})\xi_k^x \\ (\overline{Y}_k - Y_{ik})\xi_k^y \end{bmatrix} \tag{7}$$

$$G_p^{(ik)} = (\overline{G}_k - G_{ik})\xi_k^g \tag{8}$$

In Equ. (7), $\overline{X_k}$ and $\overline{Y_k}$ are the normalized x and y coordinate vector values. The appearance matrix is described by combining these both gray and shape parameters as defined as follows,

$$A_{ik} = \begin{bmatrix} S_p^{(ik)} w_{ik} \\ G_p^{(ik)} \end{bmatrix} \tag{9}$$

$S_p^{(ik)}$ and $G_p^{(ik)}$ are the shape and gray parameters, and w_{ik} is the weight value related to the shape parameter. The obtained shape and grey parameters are subjected to decomposition to generate a vector of appearance parameters as follows:

$$A_{ik} = E_{ik} a_{ik} \tag{10}$$

In Equ. (10), E_{ik} and a_{ik} are eigenvectors and vector of appearance parameters, respectively.

3.3 Support Vector Machine (SVM)

The use of hyper planes to define decision boundaries separating between data points of different classes is the key design of SVMs [26], which were originally developed for binary classification problems. Both simple, linear, classification tasks, as well as more complex, i.e. nonlinear, classification problems are able to be handled by the SVMs. In the linear and nonlinear case, both separable and non separable problems are handled by SVMs. To map the original data points from the input space to a high dimensional, or even infinite-dimensional, feature space such that the classification problem becomes simpler in the feature space is the chief idea behind SVMs. By an appropriate choice of a kernel function the mapping is done.

Consider a training data set $\{x_i, y_i\}; i = 1,2,\cdots N$, where x_i is the input vectors and y_i is the class labels $y_i \in \{-1,+1\}$. The hyper-plane in the feature space is defined as $w.x + b = 0$, where w finds an orientation of the hyper plane, x is a point lying on the hyper plane and b is the bias of the distance of hyper plane from the origin. SVMs aim at constructing a hyper-plane with maximal distance

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between the two classes and it is based on the maximum margin principle. The SVM classifier starts from the following formulations

$$\begin{aligned} w_i.x_i + b \geq +1 \quad & for \ y_i = +1, \\ w_i.x_i + b \leq -1 \quad & for \ y_i = -1, \end{aligned} \tag{11}$$

These formulations are further defined as

$$y_i(w_i.x_i + b) \geq 1 \quad i = 1,2,\cdots N \tag{12}$$

Data of both classes are overlapping in most real-life applications, which build an ideal linear separation not possible. So, a controlled number of mis-classifications should be tolerated around the margin. The resulting optimization problem for SVMs, where the violation of the constraints is penalized, is written as

$$\min \frac{1}{2}\|w_i\|^2 + C\sum_{i=1}^{N}\xi_i \tag{13}$$

Such that

$$\begin{aligned} &\sum_{i=1}^{N} w_i.x_i \geq \left(\frac{1-\xi_i}{y_i}\right) - b, \quad i = 1,2,\cdots N \\ &\xi_i \geq 0, \ i = 1,2,\cdots N \end{aligned} \tag{14}$$

where C is a positive regularization constant or cost function, which define the trade-off between a large margin and mis-classification error. The optimization problem in (13) is referred to as the primal optimization problem. Lagrangian with Lagrange multipliers $(\alpha_i \leq 0)$ are used in SVMs and can be written in the dual space. Finally, the SVM classifier classification decision function with Lagrange multipliers is stated as,

$$f(x) = sign\left(\sum_{i=1}^{N}\alpha_i y_i K(x, x_i) + b\right) \tag{15}$$

Where $K(x, x_i)$ is a positive definite kernel function, it satisfies Mercer's condition $K(x, x_i) = \varphi(x)\ \varphi(x_i)$ this is called as kernel trick. The kernel function is utilized to enable the SVMs, to work in a high dimensional feature space. Here we have utilized a Radial Basis Function (RBF) for constructing the SVM.

3.4 Optimization of SVM by PSO

To obtain a precise recognition the Support Vector Machine (SVM) parameters are simultaneously optimized by PSO technique. The SVN parameters optimization by PSO technique is shown in Fig. 2. The process of SVM optimal parameters selection by PSO is described as follows,

❖ **Initialization:** in PSO, initially the particles are randomly generated within the interval of $[n, m]$. The defined particles are composed of the SVM parameter w_i, are represented as $p = \{w_0, w_1, \cdots w_i\}; i = 1,2,\cdots N$.

❖ **Parameters:** In PSO, the particles position, velocity, learning parameters, inertia, weight and maximum number of iterations are defined.

❖ **Fitness Function:** Every particle's fitness value is calculated by using the formula which given in Equ. (13). The particles that have minimum fitness value is selected as the best particles.

❖ **Velocity and Position**: Based on the pbest and gbest values, the particles velocity and positions are updated by exploiting the Eqn. (9) and (10).

$$V_i^{(n+1)} = \omega^n V_i^n + C_1.r_1.(p_i - x_i^{(n)}) + C_2.r_2.(g_i - x_i^{(n)}) \tag{16}$$

$$x_i^{(n+1)} = x_i^{(n)} + \delta V_i^{(n+1)} \tag{17}$$

In Eqn. (16) C_1, C_2 are the learning factors, ω, δ represents the inertial weight and constraint factor, rand is positive random number between 0 and 1, $V_i^{(n)}$ is the velocity of i^th^ particle at iteration n, $x_i^{(n)}$ is the current position of the particle i at iteration n, p_i is the position of the best fitness value of the particle at the current iteration and g_i is the position of the particle with the best fitness value in the swarm.

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Stopping Criteria: The process is repeated until the maximum number of iterations is reached.

IV. EXPERIMENT AND RESULT

In this section, the experimental outcome is described in detailed, which is implemented in PC with 3.2GHz Pentium Core i5 processor using MATLAB (version 7.2). To evaluate the effectiveness of the proposed method, the performance of proposed algorithm is evaluated on the reputed video Face datasets like UPC Face Database and YouTube Face sets (YTF).The performance of the proposed algorithm is also experimented for still images by selecting two well-known face database sets like ORL, and Yale B.

For examining the performance of the proposed system, All the four extensively applied datasets: UPC, YouTube, ORL and Yale B are used. The detailed description about the acquired datasets is described in Table 1.

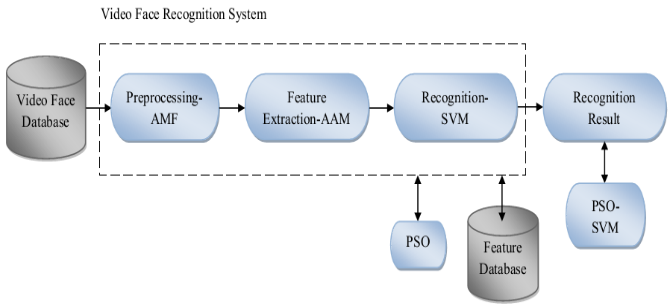

Figure 1: Structure of our proposed video face recognition system based on PSO-SVM

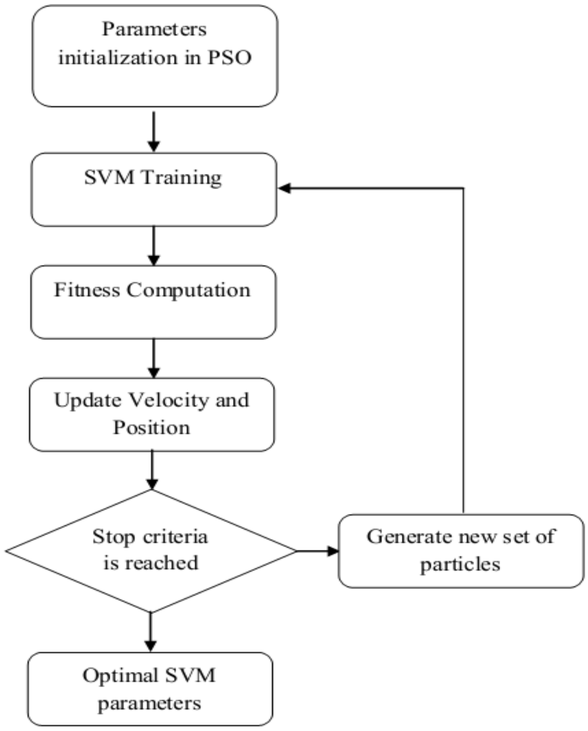

Figure 2: SVM parameters optimization by PSO

Table 1: The Databases and the data samples used in our experiments

Datasets	Identiti	Images	Images	Image	Images
ORL	40	400	10	92 x 112	JPEG
UPC(GTAV Face)	44	704	16	240 x 320	BMP
YouTube face (YTF)	50	700	14	320 x 240	JPEG
Labelled faces in the wild (LFW)	50	700	14	250 x 250	JPEG
Yale B	10	5760	15	320 x 320	JPEG

4.1 Experiment with GTAV (UPC Video Face dataset)

Initially, we have selected video frames for Noise removal as a pre-process. In pre-processing the noise from the image frames are removed by the adaptive median filtering technique. Afterward, these pre-processed video frames are subjected to feature extraction process. This is carried out by extracting

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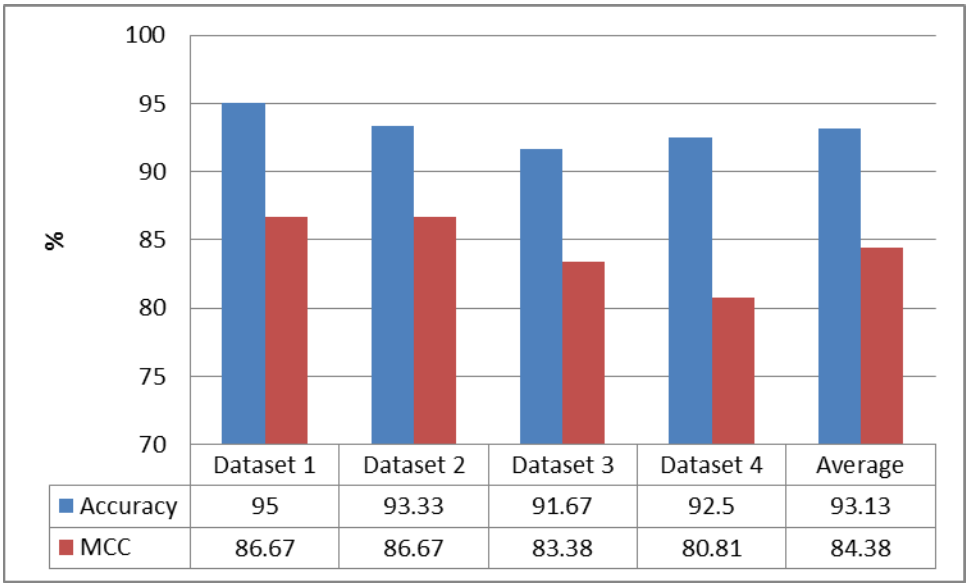
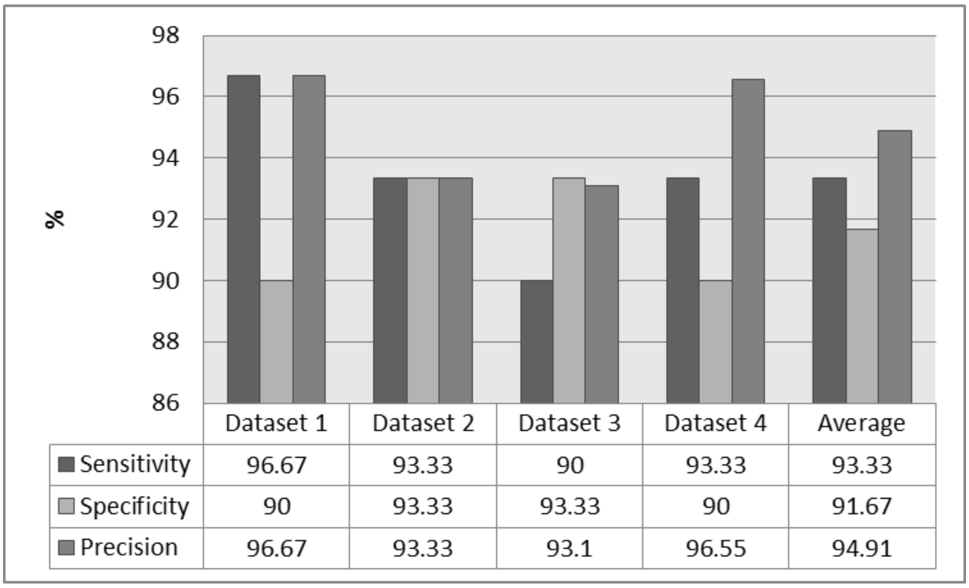
the AAM feature from each frame in the set before the training phase. The AAM features are stored in the feature vector and the same is used in SVM training and testing process. During the SVM training and testing the SVM parameters are optimized by the PSO technique. The optimized parameters in SVM by PSO automatically increase the recognition accuracy.

For experiment purpose we have created four datasets using UPC database. Each dataset contains video sequence of ten people with 16 frames in each ID with different Poses and illuminations. Each dataset is evaluated independently using confusion matrix. The result of experiments is shown in Figure 3.

The result shows a maximum accuracy of 95.00%, Maximum MCC of 86.67% and an average Accuracy of 93.13% and an average MCC of 84.38%. The Figure 3 shows the comparative analysis of recognition performance.



(a)



(b)

Figure 3: Comparative analysis on a) accuracy and MCC b)Sensitivity, Specificity, Precision

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4.2 Face recognition With YouTube Faces

The experiment is extended to YouTube Face (YTF Video Face) or face identification. For the experimental purpose we create seven Datasets selecting the videos of Individuals from YouTube Database. Dataset 1 contains videos of two people, Dataset 2 contains videos of three people, Dataset 3 contains videos of four individuals, Dataset 4 contains videos of five individuals, Dataset 5 contains videos of six individuals, Dataset six contains videos of seven people and finally the dataset 7 contains videos of eight individuals. To form the Dataset we have select the video of known individuals, separated each frame from the video and labelled the frame set. Then these labelled sets are used for training the SVM and at the same time of training the SVM parameters are optimized with PSO. Then calculated all the statistical measures as shown in the Table 2 using confusion matrix for each Dataset separately.

From the evaluation process we are able to obtain a maximum accuracy of 95 % from Dataset 7 which contains frame sets of eight individuals. We further experimented by adding videos more individuals in to the set and able to get a maximum accuracy of 95.00%. No change is observed further when we added more individual in to the set.

Table 2: Recognition result with YTF Video Face

Statistical Measures	Data set 7	Data set 6	Data set 5	Data set 4	Data set 3	Data set 2	Data set 1
	Eight *ID's*	Seven *ID's*	Six *ID's*	Five *ID's*	Four *ID's*	Three *ID's*	Two ID's
Sensitivity	**96.00**	**96.00**	**94.00**	**94.00**	**92.00**	**88.00**	**86.00**
Specificity	**94.00**	**92.00**	**94.00**	**92.00**	**92.00**	**88.00**	**84.00**
Precision	**94.12**	**92.31**	**94.00**	**92.16**	**92.00**	**88.00**	**84.31**
Negative Predictive	**95.92**	**95.83**	**94.00**	**93.88**	**92.00**	**88.00**	**85.71**
False Positive Rate	**06.00**	**08.00**	**06.00**	**08.00**	**08.00**	**08.00**	**16.00**
False Discovery Rate	**05.88**	**07.69**	**06.00**	**07.84**	**08.00**	**08.00**	**15.69**
False Negative Rate	**04.00**	**04.00**	**06.00**	**06.00**	**08.00**	**08.00**	**14.00**
Accuracy	**95.00**	**94.00**	**94.00**	**93.00**	**92.00**	**88.00**	**85.00**
MCC	**88.07**	**88.07**	**88.00**	**86.07**	**84.00**	**76.00**	**70.01**

Table 3. FR with ORL database and YALE B Database

Database	Accuracy (%)						
	Number of Training samples						
	Two training	Three training Samples	Four training samples	Five training samples	Six training samples	Seven training samples	Eight training samples

	Samples						
ORL	85.1	87.32	89.61	90.89	92.14	93.89	94.01
Yale B	67.86	72.01	74.50	78.59	81.80	84.25	86.82

Table 4: Comparison of proposed PSO-SVM based FR with different FR methods on UPC Database

Performance Metrics	PSO-SVM	LLR-SVM[26]	GLR-KNN [25]	Standard SVM [24]	ANN[24]
Sensitivity	**96.67**	93.00	88.00	90.00	70.00
Specificity	**93.33**	94.00	87.00	80.00	80.00
Precision	**93.55**	93.94	87.13	81.82	77.78
NPV	**96.55**	93.07	87.88	88.89	72.73
FPR	**06.67**	06.00	13.00	20.00	20.00
FDR	**06.45**	06.06	12.87	18.18	22.22
FNR	**03.33**	07.00	12.00	10.00	30.00
Accuracy	**95.00**	93.50	87.50	85.00	75.00
F1 Score	**95.08**	93.47	87.56	85.71	73.68
MCC	**90.05**	87.00	75.00	70.35	50.25

Table 5: Recognition Rates (%) on Different Poses on UPC Video database

Pose angle/Methods	0°	+30°	-30°	+45°	-45°	+60°	-60°	Avg
PSO-SVM	95.00	93.33	93.33	92.5	92.5	85.00	80.00	**91.55**
LLR-SVM[26]	93.50	93.50	89.50	83.16	81.67	67.5	66.00	**82.11**
GLR-K-NN [25]	92.00	91.50	88.00	77.50	77.50	62.5	56.90	**77.99**
Standard SVM [24]	90.00	85.00	83.33	83.16	80.00	77.00	78.50	**82.43**
Neural Network [24]	80.00	75.00	75.00	72.5	71.5	66.50	61.00	**71.64**

4.3 Face recognition on still images With ORL and Yale B datasets

The performance of the Proposed method is then tested on two more different databases, ORL and Yale B. For experiments, we have prepare again 7 datasets with set with two ID's, three ID's, four ID's, five ID's, six ID's, seven ID's and eight ID's from both ORL and Yale B databases separately as shown in the table 3. From the process of experiment we are able to obtain a maximum accuracy in the case of eight training samples. 30 different iteration are conducted on each of the selected data bases and the average result is reported

The Result shows a maximum accuracy of 94.01% with ORL database and 86.82% with Yale B database.

4.4 Comparison and Analysis of Recognition result with previous work

For the comparison of performance of the proposed algorithm with our previous work we use UPC Video Database. The proposed PSO-SVM algorithm

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is compared with few existing algorithms such as standard ANN based face recognition [24], standard SVM based face recognition [24], GLR and K-NN based Face Recognition [25], LLR and SVM based Face Recognition [26]. For this experiment we have created a Dataset with ten individuals and 16 images in each ID. The comparison results are recorded and are tabulated in Table 4.

From the table 4, its clear that the proposed algorithm shows highest accuracy of 95.00%

4.5Comparison of Face Recognition result with different Pose angle

In this section, the proposed PSO-SVM algorithm is compared with ANN based face recognition [24], standard SVM based face recognition [24], LLR and SVM based Face Recognition [26], GLR and K-NN based Face Recognition [25]. We have conducted 40 independent iterations for each method and an average accuracy is recorded for each pose angle of (0°, ±30°, ±45, ±60°, 90°). The comparison result is shown in Table 5.

From the result it is clear that, the proposed PSO-SVM based recognition technique attained a maximum accuracy of 95% and an average accuracy of 91.55% in this experiment Comparison result clearly indicates that the proposed PSO-SVM method show better performance compared to all other methods.

4.6 Analysis on Computation time with UPC Video database

In this section, We analyze the computation speed of recognition. The proposed PSO-SVM video face recognition speed is also analyzed in terms of computation time. Here we are also comparing the computation speed of existing FR algorithms with the proposed method. The proposed PSO-SVM algorithm is compared with ANN based face recognition [24], standard SVM based face recognition [24], LLR and SVM based Face Recognition [25], GLR and K-NN based Face Recognition [26]. The recorded computational times of the proposed method and existing methods are tabulated in Table 6.From the Table 6, it is clear that the PSO-SVM is faster in recognizing the Faces compared to the selected existing algorithms. The analysis graph is shown in Figure 8. Moreover, the proposed PSO-SVM video face recognition system performance is also analyzed in terms of their computation time. The computed computational times of our proposed method and existing methods are tabulated in Table 6.

Table 6: Computation time on UPC Video database

Experiment No.	I. I. **Proposed** I. **PSO-SVM**	IV. V. **LLR-SVM** VI. **[26]**	VII. III. **GLR-KNN** IX. **[25]**	X. XI. **ANN** II. **[24]**
1	0.036011	04.5000	04.67961	08.1322
2	0.047519	06.6456	05.7800	09.7772
3	0.056591	06.4567	06.5018	10.5866
4	0.054959	06.7654	06.8294	10.7222
5	0.058237	06.9780	07.1849	10.1094
6	0.049964	06.7653	06.7121	10.6153
7	0.048922	05.4887	05.79376	09.4988
8	0.050033	05.9856	07.51872	11.1353
9	0.036495	04.9399	05.74058	08.6391
10	0.055194	06.8909	07.79030	11.4592

As can be seen from Table 6, the proposed PSO-SVM face recognition technique has attained very less computational time than the existing face recognition methods. Comparing the four different face recognition methods, the ANN based Face recognition [17] has acquired high computational time than other three methods. From the experiment it is clear that the proposed method outperforms the

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remaining three methods in terms of recognition speed.

4.7 Comparison with state-of-art methods

In this section we have compared the proposed FR with 9 recent and popular Face recognition algorithms for comparison purpose. The experiment is conducted on You Tube Video Face Database (YTF) . The result of recognition is tabulated in Table 7 . From the experiment the proposed PSO-SVM based FR recorded a maximum accuracy of 95.00%.

5. CONCLUSION

In this paper, we proposed a video face recognition technique which recognizes face images effectively. Initially, the noise is removed from the frame using AMF and the noise free frames are given to the feature extraction process. In feature extraction, the AAM based features were extracted and given to the SVM. During the face recognition, the SVM parameters were optimized by the PSO technique. The performance of the proposed video face recognition technique was compared with few existing techniques. Experimental results show that the proposed video face recognition technique is more accurately recognizes the face images with PSO-SVM methods.

Table 7 :Face Verification on YouTube Faces DB

No	Method	YTF
1	***Proposed PSO – SVM based FR***	***95.00%***
2	SeqFace, 1 ResNet-64[17]	98.12%
3	ArcFace + MS1MV2 + R100 [18],	98.02%
4	CosFace [19]	97.60%
5	Light CNN-29 [21]	95.54%
6	Git Loss [22]	95.30%
7	FaceNet [23]	95.12%
8	SphereFace [24]	95.00%
9	DeepId2+[25]	93.20%
10	3DMM face shape parameters + CNN [26]	88.80%

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