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Face Recognition Technique Based on Active Appearance Model and Support Vector Machine

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***Abstract:** One of the active research areas for computer vision researchers is Face recognition. Active appearance model (AAM) is one of the most popular model-based methods that have been extensively used to for face feature extraction. Support vector machine (SVM) is a one common machine learning algorithm, which has been used to solve complex classification problems. A face recognition approach is proposed in this paper. The proposed technique comprises two main stages: feature extraction and classification. Active appearance model is used for feature extraction and PSO-SVM is used for the classification stage. In the experimental results, we used three benchmark datasets YALE, FERET and CASIA dataset. The results showed that the proposed technique was efficient in accuracy performance and outperformed than PSO-SVM and OPSO-SVM methods.*
***Keywords:** face recognition, Active appearance model, support vector machine, particle swarm optimization.*

1. INTRODUCTION

Face recognition is a dynamic research area because it is a natural, practicable, and non-intrusive, which is unlike from other methods of recognition such as fingerprint and iris. Face recognition is useful in numerous applications such as, identification for home security, ATM recognition or combine it with a smart card as a verification method, video examination for security [1] [2]. Face recognition is a moral cooperation between realism and social reception, and balances security and confidentiality well [3]. The Active Appearance Model (AAM) by [5] details the appearance of the face and it builds statistical model of shape and appearance of any given object. It has been widely applied for modelling the shape and appearance of human face [4]. Recently, several face recognition techniques have been developed and applied for example [6] has been proposed a face recognition technique uses an active appearance model as feature extraction method. They modified the fitting part in AAM by introducing a modified version of an artificial bee colony algorithm (ABC). However, ABC algorithm was slow in the fitting process comparing with the standard active appearance model. Another approach based on support vector machine has been developed by [7],[8]. Their approach used support vector machine in the classification process and achieved effective results. a search method called a multi-objective uniform design (MOUD) have presented by [9] which is an optimized classifier with SVM and then used the optimized SVM as classifier to face images. [10] Have introduced an elastic clustering technique to investigate multilevel subspace to enhance the recognition performance. By combining "support vector machine" and "particle swarm optimization", [11] introduced a face recognition technique called (PSO-SVM). In their proposed method, PSO was used to simultaneously optimize SVM parameters. The approach was robust and stable in terms of recognition performance. Though, the area of face recognition is still have a room of improvements and so that we propose a face recognition approach named (AAM+PSO-SVM) based on the standard active appearance model as a model-based feature extraction method and PSO-SVM as a classification method.

2. The Proposed Method

The proposed method AAM+PSO-SVM used to recognize face images under different lighting conditions. The feature extraction process is attained by Active appearance model technique (AAM) and the classification process by PSO-SVM technique. Those stages are performed successively and the images are recognized professionally. The proposed face recognition structure is shown in figure 1:

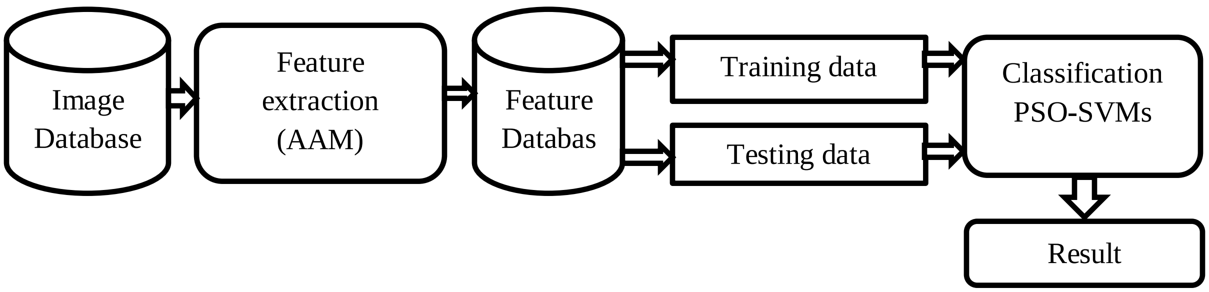


Figure 1.1 Face Features Extraction using Active Appearance Model**.**

Cootes et al. [5] has been proposed the “Active appearance model (AAM)” which has been used for feature extraction. Recently, many applications utilize AAM method for feature extraction, such as understanding human behaviour using face modelling, and medical imaging projects, like recording in functional heart imaging.

Mainly, AAM model can built in four parts: (i) A statistical shape model is built using a number of labelled training images; (ii) To model the variations of texture, a texture model is assembled which is represented by pixel intensity; (iii) An appearance model is built by combining the shape model and texture model [5]. (iv) Finally, the combined model is fitted with target image. Figure 1.2 explains the main parts of AAM.

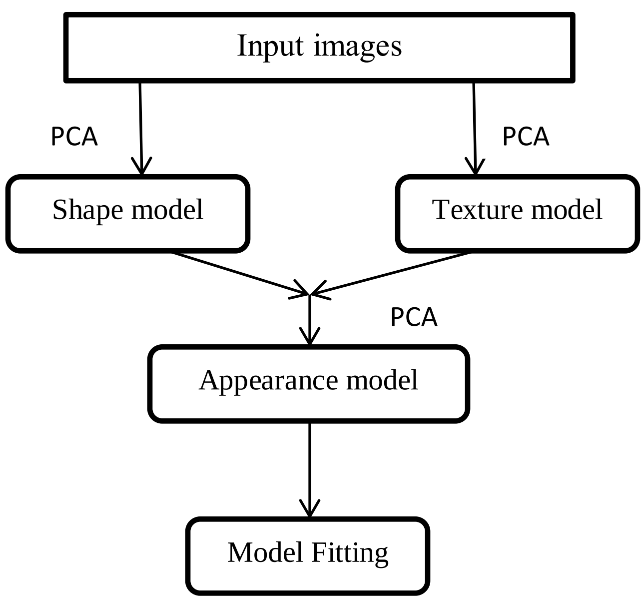


Figure 1.2 The basic parts of Active Appearance Model**.**

i. Statistical Shape Model

A shape model is constructed from a set of marked training images. A shape in 2-D case is characterized by concatenate vectors of n-point {(xi; yi)}

$$x = (x1, x2, \ldots\ldots, X_{n,} y1, y2, \ldots\ldots\ldots, y_n)T$$

Then, the shapes that are constructed will be normalized by "Procrustes analysis process" [5] and projected on the shape subspace that is generated by "principle component analysis PCA",

$$x = \bar{x} + P_s . b_s$$

where $\bar{x}$ represents mean shape, Ps = {si} is a matrix contains a set of orthonormal base vectors si and drawing the modalities of variations that extracted from the training set, and b_s made of shape variables in shape subspace. Thus, depends on the equivalent points, the images in training stage are warp to the mean shape to get "shape-free patches".

ii. Statistical Texture Model

The texture model is established more identically as the shape model. Depends on the shape model, the texture can be scanned into a vector g, and followed by process of linear normalization of texture, by the parameters $u = (\alpha, \beta)T$ and g is given by

$$g = \frac{(g_i - \beta.1)}{\alpha},$$

where α and β are, correspondingly, represents mean and variance of the texture g, and 1 = [1; 1, …..1] T is vector with the identical length of g_i . Ultimately, depending on principle component analysis (PCA), texture is estimated on the texture subspace

$$g = \bar{g} + P_g . b_g$$

where $\bar{g}$ indicates to mean texture, $P_g = \{g_j\}$ represents matrix contains a set of orthonormal base vectors g_j and defining modes of variation resulting from the training set, and b_g comprises texture parameters of the texture subspace.

iii. Combined Appearance Model

In this stage, the joined relationship between the created shape and texture is examined by PCA and the appearance subspace is produced. The shape and the appearance can be labelled as follows:

$$x = \bar{x} + Q_s . c$$
$$g = \bar{g} + Q_g . c$$

Where c represents vector of appearance parameters that control the shape and the texture together, and Q_s , Q_g are respectively matrices describe modes of variation resulting from the training set.

Accordingly, the finishing appearance model can be characterized as b = Qc where:

$$b = \begin{pmatrix} \frac{w_s b_s}{b_g} \end{pmatrix} = \left(\frac{w_s(p_s)T(x-\bar{x})}{(p_g)T(g-\bar{g})}\right)$$

and Q is representing the matrix of eigen vectors of b.

iv. Model Fitting

After creating the appearance model, it is significant to fit the created model with new images, which is vital to find the most suitable parameters of the model. However, this consider as an unconstrained optimization problem, which is more complex and challenging to solve. Usually, it can be addressed via “gradient descent algorithm”. Let p indicate the AAM parameters vector $(\mathrm{p}^{\mathrm{T}} = \mathrm{c}^{\mathrm{T}}/\mathrm{t}^{\mathrm{T}}/\mathrm{u}^{\mathrm{T}})$, which is represents combination of the appearance parameters c, the texture transformation parameters u. and pose parameters t.
Besides, g_{c} is represents the sampled texture vector of the current image, which is estimated to the texture model frame, and $\mathrm{g_m}$is represents the texture vector, produced via the model. There is a linear relationship between the texture difference between an image and the model and the variance of p which is given by:

$$\delta_p = R.r(p),$$
$$r(p) = g_c - g_m \;,$$

where, δp is a lesser variance of p, and R is represents the linear relationship (or gradient matrix) between δp and r. AAM assumes that R be fixed and computes it by multivariate linear regression methods. Since the relationship R is computed, fitting is an iterative procedure that can be carried out as follows (Gao et. al. 2010).

The texture of an image is sampled and projects it to texture model space.
Compute the residual texture vector, $l = g_{\mathrm{i}} - g_{\mathrm{m}}$ and assess the fitting correctness using $E = |l|2$, where |.| mean the norm (2-norm generally).

Derived variance of parameters of the model by $\delta_p = -R.\, l(p)$.
Update model parameters p → p + kδp, where k = 1 at first.
Through the new model parameters, compute the new model texture g_m^-, and the texture, g_i^- is resampled
Compute the new residual vector, $l^- = g_i{}^- - g_m{}^- \; and \; E^- = |l^-|\, 2$.
If E^-< E, then accept the update; if not, try at k = 0.5, 0.25, etc., at that time go to the first step.

These procedures repeat till there is no more enhancement.

1. Classification using PSO-SVM

“Support vector machine” (SVM) is supervised learning approach, which is very useful for classification and regression process [12]. Though, the selection process of the training parameters is influencing factor effects on the performance of SVM. SVM classifier is based on statistical learning theory, which is aimed at determining a hyperplane which efficiently separates two classes by using training dataset. Suppose that, a training dataset $\{x_i, y_i\}_{i=1}^{n}$, where x is represents the input vector, and y ∈ {+1,- 1} is class label. This hyperplane is defined as: w. x + b = 0, where x is a point on the hyper plane, w represents the positioning of the hyper plane, and b is bias of the distance of that hyper plane from the origin. As shown in Figure 5.1, the optimal splitting hyper plane could be found by minimizing $\|w\|^2$ under the constraint $y_i(w.x_i + b) \geq 1, i = 1,2, \ldots\ldots, n$.

Accordingly, determination of optimal hyperplane is essential for solve the optimization problem that given by:

$$\min \ \frac{1}{2}\|w\|^2$$
$$y_i(w.x_i + b) \geq 1, i = 1,2, \ldots \ldots, n$$

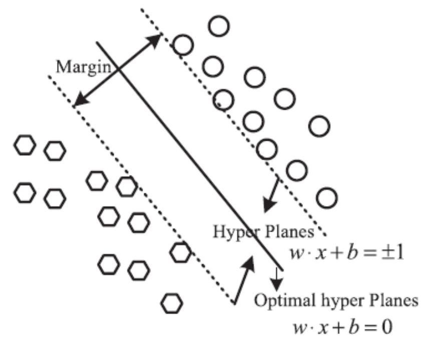


Figure 1.3 The classification process of SVM.

The positive slack variables ξ_i, ξ_i^* are presented to substitute the optimization problem, and the method could be extended to allow for nonlinear decision surfaces, the new optimization problem is given as:

$$\min_{w,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi$$

$$y_i(w.x_i + b) \geq 1 - \xi, \xi \geq 0, i = 1,2, \ldots \ldots, n$$

$$\text{Such that} \quad \sum_{i=1}^{N} w_i x_i \geq \left(\frac{1-\xi_i}{y_i}\right) - b, i = 1,2, \ldots N$$
$$\xi_i \geq 0, i = 1,2, .. N$$

Where, C is indicates to the penalty parameter or regularization constant. The penalty parameter controls the tradeoff between two competing criteria of error minimization and margin maximization. Therefore, the classification decision function can become:

$$f(x) = \operatorname{sign}\left(\sum_{i=1}^{n} \alpha_i y_i K\left(x_i, x_j\right) + b\right)$$

Where, α_i represents the Lagrange multiplier, and the kernel function is $K(x_i, x_j) = \emptyset(x_i)\emptyset(x_j)$, which can map the data into a higher dimensional space through some nonlinear mapping functions $\emptyset(x)$.Radial basis function (RBF) indicated as $\exp(-\|x_i - x_j\|/2\sigma^2)$, σ is a real positive number which is usually used in the classification of images, hence, the RBF is used to create SVM in this research.

2. Parameters selection of SVM using PSO

"Particle swarm optimization" PSO mimics the swarm behavior of individuals which represent probable solutions in a D-dimensional search space. Particle i is contain four vectors: $X_i = (x_i{}^1, x_i{}^2, \ldots, x_i{}^D)$, where $x_i{}^D$ represents its position in the dth dimension; $Pbest_i = Pbest_i{}^1, Pbest_i{}^2, \ldots, Pbest_i{}^D)$, where $Pbest_i{}^D$is the finest position in the dth dimension that particle i has found on its own; $V_i = (v_i{}^1, v_i{}^2, \ldots, v_i{}^D)$, , where $v_i{}^D$ indicate to the velocity in the dth dimension; and $gbest_i = gbest_i{}^1, gbest_i{}^2, \ldots, gbest_i{}^D)$, where $gbest_i{}^D$ is the global best position in the dth dimension for all particles. In the swarm, particles move over the search space as follows:

$$V_i{}^d = wV_i{}^d + m_1k_1.\left(Pbest_i{}^d - z_i{}^d\right) + m_2k_2.\left(gbest_i{}^d - z_i{}^d\right)$$

$$z_i{}^d = z_i{}^d + V_i{}^d$$

where w is represents the inertia weight,m_1 and m_2 are velocity coefficients which come as a constants with the value of 2.0, $k_1$and k_2 are random numbers with the range of [0.1] at each iteration from d=1 to D, $V_i{}^d$ is indicate to the velocity of the ith particle, $z_i{}^d$is the present location of the particle i, $Pbest_i{}^d$ is represents the location of the finest fitness value of the particle at the present iteration and $gbest_i{}^d$ is represents the location of the particle with the finest fitness value in the swarm.

3. Parameters Optimization of SVM by PSO

The parameters of SVM are optimized by PSO procedure to attain a precise recognition result. The SVM optimization process by PSO is described in the figure as below:

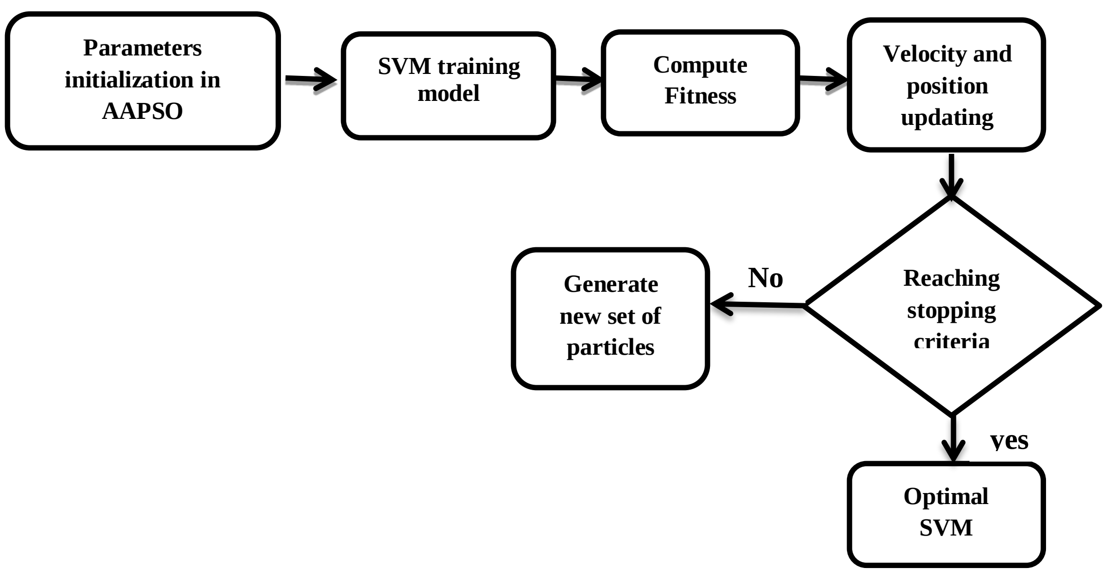


Figure 1.4 Parameter optimization of SVM using PSO.

3. EPERIMENTAL RESULTS

The proposed technique executed in the MATLAB platform. The proposed method is assessed with three face datasets YALE, CASIA and FERET under different lighting conditions. In our technique the face images are tested with two conditions as follows:

• Face images with same illumination

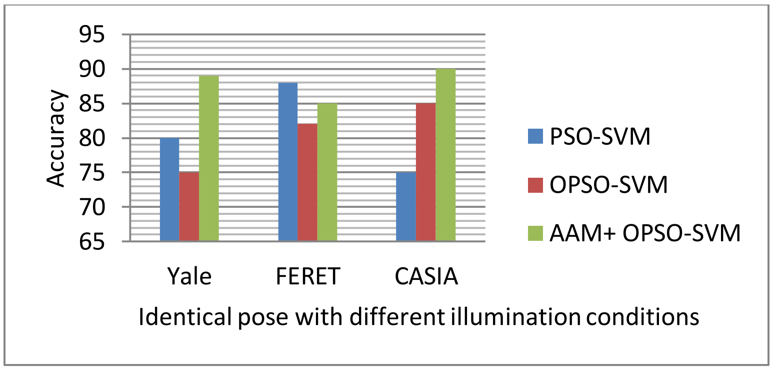
• Face images with different illumination

The three datasets are divided into training and testing datasets. In Yale dataset, there are 15 classes, in each class there are different images in different illumination conditions. In the experimental tests, 165 images have been used in the evaluation process 75 images for training and 90 images for testing. From CASIA database, 500 images have been used and have been separated to five datasets. In each dataset, there are 100 images at five illumination variations while FERET dataset, same thing as CASIA has been done for FERET dataset. Figure 1.3 shows examples of images for the three datasets. In the evaluation process, the images in each datasets have been equally divided for training and testing. In order to demonstrate the efficiency and the stability of the proposed method, the facial images have been assessed on two conditions: (i) identical pose with different illumination conditions (ii) identical pose with the same illumination. To achieve the performance analysis process, we have performed the different rounds of experiments by AAM+PSO-SVM method. The Table 1.1 and Figure 1.4 illustrate the accuracy of outcomes generated by the proposed face recognition method (AAM+PSO-SVM) against the existing OPSO-SVM and PSO-SVM face recognition approaches.

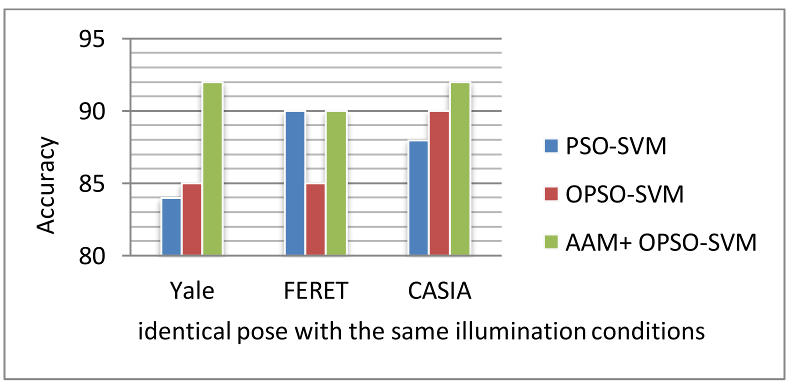
Figure 1.5 Sample images for each dataset: (a) Yale dataset (b) CASIA dataset (c) FERET dataset.

Table 1.1: Accuracy values of the proposed AAM+PSO-SVM technique with three datasets.

Conditions	Condition description	Yale Dataset		FERET Dataset		CASIA Dataset	
1	identical pose with different illumination conditions	Method	Accuracy	Method	Accuracy	Method	Accuracy
		PSO-SVM	80	PSO-SVM	88	PSO-SVM	75
		OPSO-SVM	75	OPSO-SVM	82	OPSO-SVM	85
		AAM+ OPSO-SVM	89	AAM+ OPSO-SVM	85	AAM+ OPSO-SVM	90
2	identical pose with the same illumination conditions	PSO-SVM	84	PSO-SVM	90	PSO-SVM	88
		OPSO-SVM	85	OPSO-SVM	85	OPSO-SVM	90
		AAM+ OPSO-SVM	92	AAM+ OPSO-SVM	90	AAM+ OPSO-SVM	92



(a)



(b)

Figure 1.6 Average accuracy performances of the proposed AAM+ PSO-SVM and PSO-SVM, OPSO-SVM methods.

4. CONCLUSION

Face recognition technique had been introduced in this paper. The proposed technique was based on two stages which were active appearance model (AAM) and PSO-SVM methods. AAM has been used to extracts the face features and those features were given to the PSO-SVM method to classify them according to the correct face class. Three different datasets have been used in the experimental results with different illumination conditions: YALE, FERET and CASIA dataset respectively. The accuracy metric has been used for the evaluation purpose. The proposed technique was outperformed than the other face recognition techniques such as (OPSO-SVM) [8] and (PSO-SVM) [11] in terms of recognition accuracy especially with YALE and CASIA database. One problem arises when we fitted the AAM model with the original face model which is that the time which can be reduced in the future work.

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