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FACE RECOGNITION TECHNIQUE BASED ON ADAPTIVE-OPPOSITION PARTICLE SWARM OPTIMIZATION (AOPSO) AND SUPPORT VECTOR MACHINE (SVM)

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ABSTRACT

OPSO and AAPSO are the most recently developed face recognition techniques, in order to optimize the parameters of SVM. However, in order to increase the optimization, a combination between OPSO and AAPSO techniques has been proposed in this paper. The proposed technique is called Adaptive-Opposition particle swarm optimization (AOPSO). In AOPSO, the random values in the initial generation of the population in PSO is solved by OPSO and the randomization fixed values in the velocity coefficient is solved using AAPSO in the same time. Then, the proposed algorithm is used with support vector machine to find the optimal parameters of SVM. The performance of the proposed AOPSO method has been validated with two face images datasets, YALE and CASIA datasets. In the proposed method, we have initially performed feature extraction, followed by the recognition of the extracted features. In the recognition process, the extracted features have been employed for SVM training and testing. During the training and testing, the SVM parameters have been optimized with the AOPSO technique. The comparative analysis has demonstrated that, the AOPSO-SVM proposed in this study has outperformed the existing PSO-SVM technique.

Keywords: face recognition, PSO, AOPSO, SVM.

1. INTRODUCTION

Classification, regression and other learning tasks can be done using a popular machine learning method known as Support Vector Machine (SVM) [1]. The SVM classifier [2, 3] is a supervised learning algorithm, which depends on statistical learning theory [4, 5]. The SVM classifier is aimed at determining a hyperplane, which effectively divides two classes by using training data sets [6]. It is noteworthy that, SVM is a highly effective technique, which focuses on the concept of increasing the margin, or level of separation, in the training data. Several hyperplanes are available, which facilitates the division of data for classification. Nevertheless, it is crucial to select optimal hyperplane, which signifies the largest separation, or margin, between two classes. SVM looks for the ideal hyperplane making use of support vectors [7]. The support vectors are the training samples, which estimate the ideal separating hyperplane; furthermore, they are the most challenging patterns to classify [8]. This means that, the support vectors comprise of the data points, which are nearest to the optimal hyperplane. As SVM deals with a subset of data points (support vectors) that are close to the decision boundary, generally the SVM solution depends on the local features of the data. Over the last ten years, SVM has triggered the interest of researchers as a contemporary machine-learning technique for solving problems in a number of fields, such as, pattern recognition, bioinformatics and other non-linear problems with small sample sizes. Fundamentally, SVM has robust theoretical framework and a superior generalization capability [9]. In terms of implementation, training an SVM in classification is similar to that of solving a linearly constrained quadratic programming (QP) problem, which utilizes considerable volume of memory and computation time, when dealing with huge volume of samples. Even though PSO-SVM [6, 10], AAPSO-SVM [11] and OPSO-SVM [12] have been widely used to address the above mentioned problems, still it has a room of an improvement in term of SVM parameters optimization. Therefore, for resolve this problem, in this study we have proposed a AOPSO-SVM method. The rest of the paper has been organized as follows: the related work has been discussed in section 2, followed by the description of our proposed method. The experimental result and analysis have been described in section 3. Finally, the conclusions and potential future studies have been presented in Section 4.

2. RELATED WORK

As discussed above, the PSO technique has been employed in several fields, such as, video-based face recognition, face verification and face recognition. In traditional PSO, the populations are randomly generated, which results in the random generation of population; this feature creates an element of doubt about accuracy of results produced by PSO. Another problem in PSO, the randomization that is occurring in choosing the velocity coefficients of PSO which is usually fixed random number.

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Consequently, a number of studies have attempted to resolve the above mentioned problems. Mohammed *et al*., [12] have proposed OPSO-SVM for the purpose of minimizing the constraint of randomization in PSO; the OPSO has been employed to enhance the parameters of the SVM. The optimized SVM has been trained for effective face recognition. In another study, and to address the problem of random values for the acceleration coefficients in PSO; [11] have proposed adaptive acceleration particle swarm optimization (AAPSO). They utilized AAPSO to optimize the parameters of SVM. In addition, many researchers have been used PSO as a part of face recognition technique. Raghavendra *et al.*, [13] have proposed a two-image fusion scheme for incorporating visible and near infrared face images (NIR), to enhance the performance of face verification; for this purpose, they have employed particle swarm optimization (PSO) to discover an ideal approach for performing fusion of the visible and NIR sub-band coefficients. For addressing the dynamic optimization problem Jean-Francois Connolly *et al.* [14] have proposed a dynamic particle swarm optimization for a video-based face recognition system. The authors have proposed an incremental learning strategy based on dynamic particle swarm optimization (DPSO), to develop heterogeneous ensembles of classifiers (where each classifier fits to a particle) in response to new reference samples. This approach has been employed to resolve video-based face recognition, using an AMCS that includes a pool of fuzzy ARTMAP (FAM) neural networks, which are used for classifying facial regions; and the enhanced version of DPSO, optimizes all FAM parameters, so that the classification rate has been maximized.

3. THE PROPOSED FACE RECOGNITION TECHNIQUE

The proposed face recognition technique is performed in three phases: feature extraction by PCA, Adaptive-Opposition particle swarm optimization (AOPSO), and parameters selection for SVM with AOPSO. These three phases have been performed repeatedly on the input database face images, and thus, the face images are recognized more effectively. The three phases are discussed in Sections 3.1, 3.2 and 3.3. The basic structure of our proposed face recognition system is shown in Figure-1.

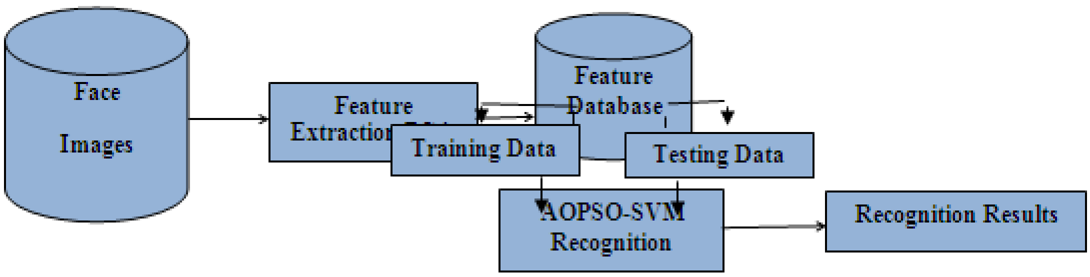

Figure-1. Structure of the proposed recognition technique based on AOPSO-SVM.

3.1 Feature extraction using PCA

The purpose of the feature extraction is to extract the information that represents the face. Principal component analysis (PCA) is one of the popular feature extraction methods [15]. Using an information theory approach, PCA has been used for feature extraction in face recognition [16]. This approach could be proficiently and easily coded to extract the appropriate information from a face image. The subspace of the image space extended by the training face image data has been identified and de-correlated, using the pixel values. The conventional representation of a face image has been obtained, by projecting the face image on to the coordinate system described by the principal components. Information compression, de-correlation and dimensionality reduction have been employed for decision making in the projection of face images into the principal component subspace. Dealing with an image as a vector in a highly dimensional face space mathematically attempts the principal components of the distribution of faces or the eigenvectors of the covariance matrix of the set of face images. We have applied PCA on the training and testing database face images and have obtained exclusive one dimensional feature vectors.

3.2 The proposed adaptive-opposition particle swarm optimization (AOPSO)

Particle swarm optimization (PSO) is inspired by the social behavior of biological creatures, such as fishes and birds, which have the ability to group together to work as a whole to locate desirable positions in a certain area, e.g., fish searching for a food source. This type of search behavior is equivalent to searching for solutions of equations in a real-valued search space [17].PSO emulates the swarm behavior of individuals who represent potential solutions in a D-dimensional search space. In the proposed AOPSO method, the populations are generated randomly as in the standard PSO and also based on opposite number (Jabeen *et al.* 2009). The opposite number generation process is described as below:

- Let $r$be the real number which is generated between the intervals $\{a, b\}$, then the opposite number$\bar{r}$ is defined by$\bar{r} = a + b - r$
- Let $p = \{r_1, r_1, \dots r_i\}$be a point, where$r_i \in \{a_i, b_i\}$ and based on these points the opposite points are defined as

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$\bar{p} = \bar{r}_1, \bar{r}_2, \ldots \bar{r}_i\}$ where
$\bar{r}_i = a_i + b_i - r_i$

By utilizing the aforementioned process, the opposition based populations are initially generated in OPSO (Jabeen *et al.* 2009). After the population generation, each individual particles fitness value is to be computed. The fitness value of $f\,(\bar{p}) \geq f(\bar{p}+1)$ and point $\bar{p}+1$ can be replaced by $\bar{p}$ otherwise we will continue with $\bar{p}+1$. To find the more fit ones the opposite point and its point are evaluated simultaneously.

Particle i is often composed of four vectors: $X_i = (x_i^1, x_i^2, \Lambda\ , x_i^D)$, where x_i^d is its position in the d[th] dimension; $pbest_i = (pbest_i^1, pbest_i^2, \Lambda\ , pbest_i^D)$, where $pbest_i^d$ is the best position in the dth dimension that particle i has found on its own; $V_i = (v_i^1, v_i^2, \Lambda\ , v_i^D)$, where v_i^d is the velocity in the d[th] dimension; and $gbest = (gbest^1, gbest^2, \Lambda\ , gbest^D)$, where $gbest^d$ is the global best position in the d[th] dimension that all particles have found. Particles in a swarm move through the search space as follows:

$$V_i^d = wV_i^d + k_1 r_1.(Pbest_i^d - x_i^d) + k_2 r_2.(gbest_i^d - x_i^d) \quad (1)$$

$$x_i^d = x_i^d + V_i^d, \quad (2)$$

r_1 and r_2 are two independent random numbers uniformly generated in the range [0.1] at each updating iteration from d=1 to D, V_i^d is the velocity of the ith particle, x_i^d is the current position of the particle i, $pbest_i^d$ is the position of the best fitness value of the particle at the current iteration and $gbest^d$ is the position of the particle with the best fitness value in the swarm. In addition, k_1 and k_2 are the adaptive velocity coefficients based on the proposed formula Adaptive PSO (Abdulameer *et al* 2014) :

$$k_1 = \frac{2}{3}(c_{1max} - c_{1min})\left(\frac{f_{\min}}{f_{avg}} + \frac{f_{\min}}{2f_{\max}}\right) + c_{1min}, \quad (3)$$

$$k_2 = \frac{2}{3}(c_{2max} - c_{2min})\left(\frac{f_{\min}}{f_{avg}} + \frac{f_{\min}}{2f_{\max}}\right) + c_{2min}, \quad (4)$$

where k_{1max} and k_{1min} represent the minimum and maximum values of k_1, f_{min}, f_{avg} and f_{max} are the particle minimum, average and maximum fitness values of the entire population, and k_{2min} and k_{2max} represent the minimum and maximum values of k_2. The proposed AOPSO algorithm is described in the following flowchart:

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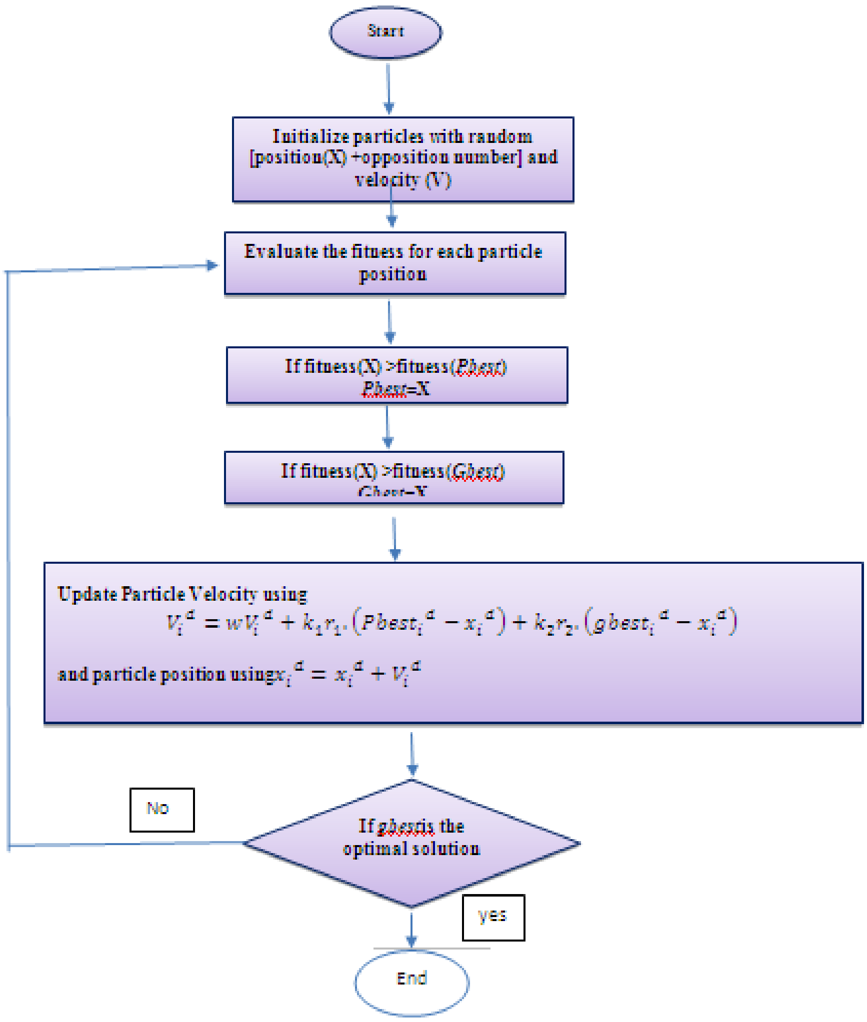

The pseudo code of the proposed AOPSO
For every particle
Initialize particle randomly+ opposite number
END
Do
For every particle in both populations
Compute fitness value and choose the fitter ones form both populations are chosen as particle.
If the Computed fitness value is better than the best fitness value (*pbest*) in history
put current value as the new *pbest*
End
Select the particle that has best fitness value among all the particles as the *gbest*
For every particle
Compute the velocity of particle using equation (1)
Update Particle position using equation (2)
End
Continue while maximum iterations or minimum error criteria is not attained

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3.3 Parameter selection for support vector machine using adaptive opposition particle swarm optimization

The SVM parameters *are* optimized using the proposed AOSPO method as shown in Figure-2.

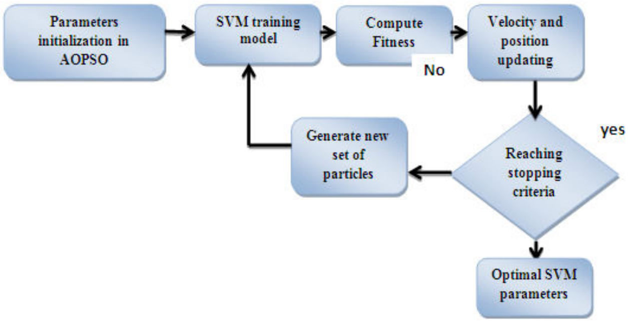


Figure-2. SVM parameter optimization using the proposed AOPSO.

The process of optimal parameter selection by AAPSO in SVM is as follows:

Step 1: Initially, the particles are generated randomly and based on the opposite number generationwithin the interval $[x, y]$. The generated particles are composed of SVM parameters p_i. Then, the parameters of each particle are initiated, including position and velocity.

Step 2: The fitness value of every particle is calculated using Equation. (5). The particles that have the minimum fitness values are selected as the best particles as follows:

$$\min \frac{1}{2}\left\|p_i\right\|^2 + C\sum_{i=1}^{N}\xi_i \quad , \tag{5}$$

$$\text{Such that} \quad \sum_{i=1}^{N} p_i . x_i \geq \left(\frac{1-\xi_i}{y_i}\right) - b, \quad i = 1,2,\Lambda\ N \tag{6}$$

$$\xi_i \geq 0, \; i = 1,2,\Lambda\ N$$

where, N is the size of the training dataset, and C is the cost function.

Step 3: The $\overline{pbest_i}$ of each particle is updated and $\overline{gbest_i}$ for the domain is updated. Based on these values, the velocity and position of every particle are updated using equations (1) and (2).

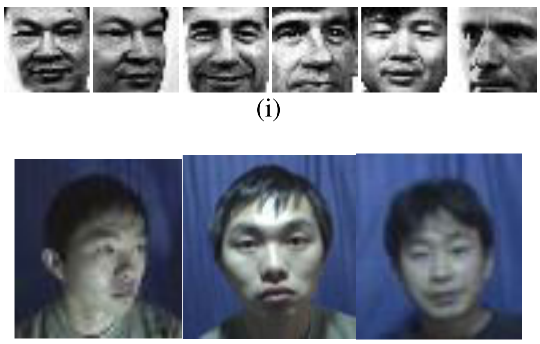
Step 4: Stop if the current optimization solution is good enough or if the stopping criterion is satisfied.

4. EXPERIMENTAL RESULTS

The proposed recognition technique has been experimented in the working platform of MATLAB. The performance of the proposed AOPSO-SVM technique has been evaluated using the YALE dataset [19] and CASIA face dataset [20].

The two datasets were divided into training and testing datasets. In Yale dataset, there are 15 classes, in each class there are different images in different conditions. In the experimental tests, 165 images have been used in the evaluation process75 images for training and 90 images for testing.From CASIA database, 500 images have been used for experimentation. In CASIA database, the images are chosen at five different poses in different environments and illumination variations. In the evaluation process, the images in the dataset have been equally divided for training and testing.

The performance of the proposed technique has been analyzed by conducting *n*-fold (n = 10) cross validation over each datasets, and the corresponding statistical performance measures are determined. To perform *n*-fold cross validation, ten folds of training and testing datasets are generated by folding operation. The images are obtained from both databases, and the feature extraction has been computed using PCA, while the recognition process has been computed using the proposed AOPSO-SVM technique. Figure-3 illustrates the sample face images from the YALE and the CASIA databases.



(i)

(ii)

Figure-3. Sample face images from (i) YALE and (ii) CASA databases.

To analyze the classification performance, we have conducted 10 experiments on the Yale and CASIA datasets. Table-1 and Figure-4 illustrate the results of classification accuracy obtained for the two dataset. In 10 experiments, our proposed AOPSO-SVM method has attained higher iris image classification accuracy, as against the standard PSO-SVM. The average classification accuracy is 86.9% for Yale dataset, and 88.3% for CASIA dataset.

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Table-1. The accuracy of PSO and AOPSO based on SVM classification performance results for the Yale and property CASIA face datasets.

Experiments	Accuracy (%) PSO-SVM	Accuracy (%) AOPSO-SVM	Accuracy (%) PSO-SVM	Accuracy (%) AOPSO-SVM
	Yale dataset	Yale dataset	2.5d dataset	2.5d dataset
1	89	92	89	91
2	81	90	80	85
3	80	85	85	90
4	70	82	87	90
5	82	80	80	85
6	80	87	85	90
7	81	90	82	85
8	82	87	80	85
9	85	86	89	92
10	80	90	85	90
Average	81	86.9	84.2	88.3

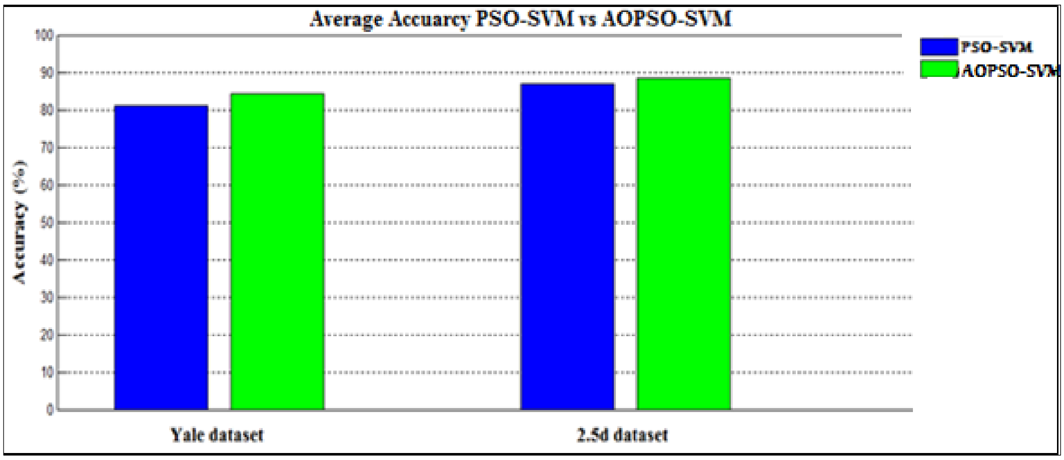
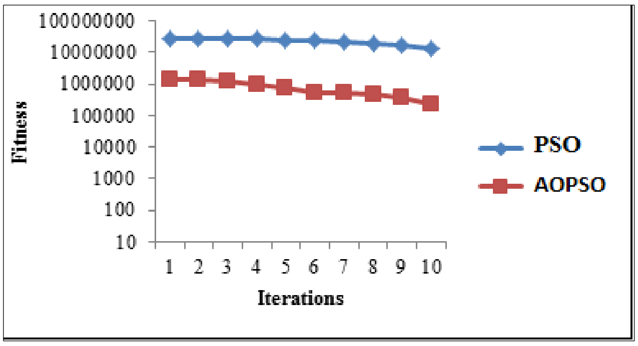


Figure-4. Average accuracy values of PSO-SVM and the proposed AOPSO-SVM.

Additionally, the performance of our proposed AOPSO method has been compared with the performance of the PSO method, Equation. (5). Based on the results illustrated in Figure-5, it is evident that, our proposed AOPSO method has yielded more accurate particles that have lower fitness values, than those generated by the conventional PSO method. The high performance result shows that, our AOPSO method is able to determine the more accurate SVM parameters.



(i)

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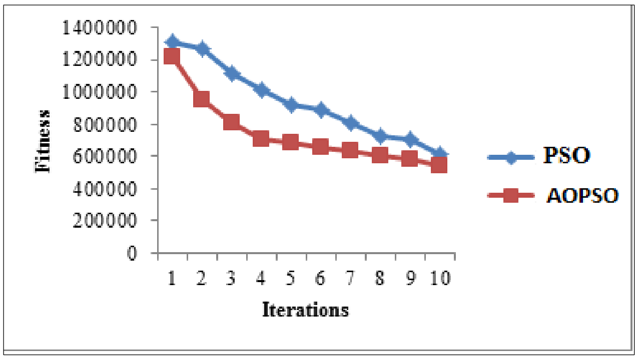

(ii)

Figure-5. Performance of AOPSO and PSO methods (i) YALE database (ii) CASIA database.

In Figure5, our proposed technique has obtained more accurate particles that have minimum fitness values, smaller than those obtained with the conventional PSO method. Therefore, our AOPSO technique has yielded more accurate SVM parameters. Figure-5(i) and (ii) show the fitness value performance for particles used on the YALE and CASIA face images databases. For all iterations, the fitness values of the particles of our proposed AOPSO method are lower than those of the conventional PSO method. Furthermore, the computational times for our proposed AOPSO and the PSO methods are shown in Table-2 and Figure-6.

Table-2. Computation times of proposed AOPSO and PSO techniques with SVM.

Computational Time (sec)		
Images	PSO	AOPSO
1	0.182345	0.133412
2	0.024352	0.019061
3	0.025007	0.020171
4	0.02178	0.014853
5	0.020261	0.017977
6	0.020363	0.020351
7	0.019325	0.017685
8	0.020612	0.018368
9	0.020936	0.01778
10	0.018513	0.017532

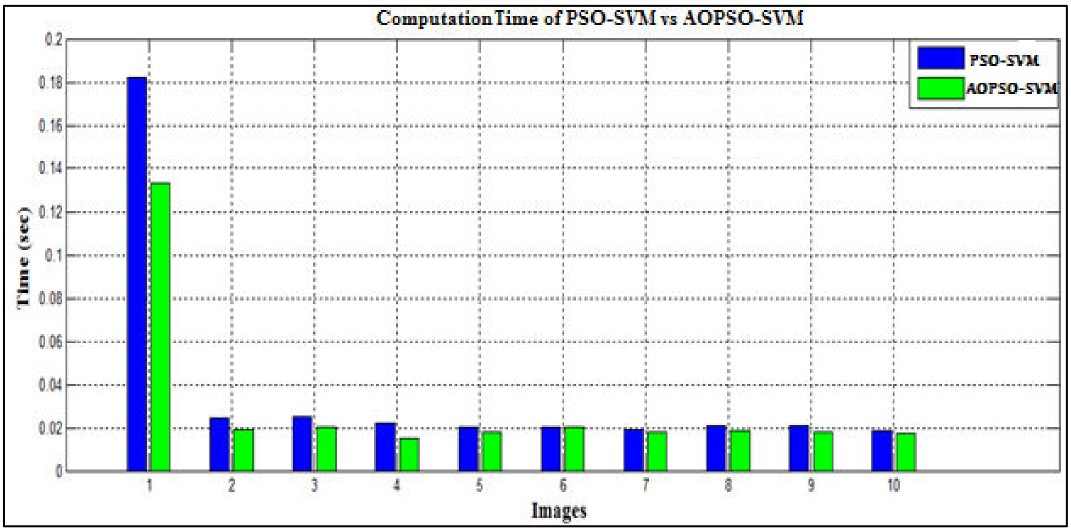

Figure-6. Computation times of proposed AOPSO-SVM and PSO-SVM techniques.

5. CONCLUSIONS

In this paper, we had introduced AOPSO based on SVM to address the limitations of the standard PSO method. These limitations of PSO: using random values in the initialization process and choosing velocity coefficients, which may lead to performance instability? The optimized SVM, using the AOPSO technique, shows effective face recognition performance. Two human face databases, YALE and CASIA were utilized to analyze the performance of our proposed AOPSO-SVM face recognition technique. The performance and comparative analysis results had showed that our proposed AOPSO-SVM technique has yielded higher face recognition performance results as against the PSO-SVM method. Based on the 10 experiments we have proved that, our proposed AOPSO method has attained higher face image average classification accuracy. The average classification accuracy was 86.9% for Yale dataset and 88.3% for ASIA dataset. In addition, the computation time of proposed AOPSO was lesser than the conventional PSO by 21%, in terms of finding the optimal parameters in SVM.

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