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Performance Analysis of Different Feature Extraction Algorithms Used with Particle Swarm Optimization for Gait Recognition System

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Abstract— ***Recently, person identification systems based on gait recognition had been gained growing large interest from researchers in the fields of artificial intelligence and image processing Thus, a gait recognition system based on particle swarm optimization (PSO) has been suggested in this work to recognize any person at a distance who performing the movement. Three feature extraction and dimension reduction algorithms were used to increase the recognition performance of PSO algorithm. These algorithms are: Liner Discriminant Analysis (LDA); Discrete Fourier Transform (DFT); and Discrete Cosine Transform (DCT). Many experiments were conducted for PSO with the three algorithms using different: swarm size, block dimension and number of iterations. Best results obtained when selecting swarm size equal 40, feature block size 70×70 and 100 number of iterations. At the same time best results of: recognition rate (97%), MSE (0.0027) and PSNR (38) where obtained when adopting LDA algorithm in comparison with DFT and DCT. And also the results obtained from DFT are better than the results obtained from using DCT. The time required for executing the LDA is lowest than the time required for executing DFT and DCT. DCT require more time than the other used feature extraction algorithms.***

Index Terms— ***Gait Recognition, Practical Swarm Optimization (PSO), Liner Discriminant Analysis (LDA), Discrete Cosine Transform (DCT), Discrete Fourier Transform (DFT)***

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I. Introduction

Person identification had been largely used by researches in recent years according to its authentication applications for computer operating systems, enterprises, mobiles phones and security systems. Token-based, knowledge-based, and biometric-based can be regarded as person identification techniques [1..3]. Gait or motion is a potential behavioral feature and coordinated, cyclic combination of movements that can be defined as a sequence of following poses that recognize people and walking. A single pose can be represented by kinematic chain. It describes the pose by a skeleton tree like structure with measured bones lengths. Gait can be captured by a stereovision system of two-dimensional video cameras of monitoring systems. There is no information about actor positions, skeleton model and its kinematic chain. Motion capture systems can acquire motion as a time sequence of poses are much more detailed and accurate [4].

Gait recognition to be the recognition of some salient property (identity, style of walk, or pathology, based on the coordinated, cyclic motions that result in human locomotion) [5].

Recently human identification at a distance has recently gained more interest from the computer vision community with the increasing demands of visual surveillance systems. This interest is driven by the need for automated person identification systems for visual surveillance and monitoring applications in banks, parking lots, and airports [6][7]. Gait recognition had been widely used to provide noninvasive way to recognize persons at a distance without requiring the person awareness and standard distance of a person in front of a camera, and controlled environment. Many literature researches were focused on gait recognition each with different approaches, strengths and limitations [8..15].

Particle Swarm Optimization (PSO) is a heuristic, population-based, search optimization algorithm that is introduced by Kennedy and Eberhart (1995) [17]. PSO is based on swarm intelligence widely used and rapidly developed to solve optimization problems in many applications [16]. Many literature researches were focused on improving the PSO [18..26]. PSO was used in many researches for solving recognizing problems such as face recognition [27][28], palmprint recognition [29..32] and human body pose estimation from still images [33]. There is lack of literature researches related to gait recognition that based on PSO.

Many feature extraction algorithms were suggested and implemented in the literature for feature extraction and reduce image dimensionality. Liner Discriminant Analysis (LDA) [34] is statistical approach to reduce dimensionality while preserving class discriminatory information as possible as. LDA computes an optimal transformation and achieving maximum class discrimination by minimizing within-class distance and maximizing between-class distance. The optimal transformation in LDA can be computed by applying an eigen decomposition on the scatter matrices [35..39].

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While Discrete Cosine Transform (DCT) is a transformation technique used in image processing [40][41] that had been introduced by Ahmed, Natarajan and Rao (1974) [40].

DCT had been used by literature researches [42..47] as a feature extraction in recognition process for dimension reduction. The Fourier transform including Discrete Fourier transform (DFT) represents primary tool of digital signal processing and plays an important role in image processing applications such as enhancement, analysis, restoration, and compression [48][49].

DFT converts a finite list of equally spaced samples of a function into the list of coefficients of a finite combination of complex sinusoids, ordered by their frequencies, that has those same sample values. It can be said to convert the sampled function from its original domain to the frequency domain. DFT is used by many literature studies for recognition applications such as iris recognition [50][51]; gait detection [53]; and face recognition [54].

According to above introduction, PSO is used in this work for gait recognition system according to its optimization features. LDA, DFT and DCT were used separately as feature extraction algorithms to increase the performance of the suggested gait recognition system. Many experiments will be conducted in this work with different PSO swarm size, number of iterations and different size of LDA, DCT and DFT feature vector. This paper is organized as follows: section II includes description of feature extraction algorithms (LDA, DFT and DCT). Section III includes description of PSO. The research methodology is included in section IV. Section V includes the experimental results. Finally section VI concludes this work.

II. Feature Extraction Algorithms

Many feature extraction algorithms can be used to extract the main features of image for recognition process.

A. Liner Discriminant Analysis (LDA)

LDA can be used to reduce dimensionality, classification and preserve class discriminatory information as much as possible. The LDA includes the following steps [34-39]:

1. Supposing set of D-dimensional samples $x1, x2, \ldots xN$, $N1$: belong to class $\omega 1$ and $N2$ to class $\omega 2$.
2. Search to obtain scalar y by projecting samples x onto line y where $y = wTx$.
3. Choice scalar that maximizes the separability of scalars of all possible lines.
4. Define measure of separation to find a good projection vector.
5. Calculate mean vector of each class in x-space and y-space according to Eq.1:

$$\mu_i = \frac{1}{N_i}\sum_{x \in \omega_i} x \text{ and } \tilde{\mu}_i = \frac{1}{N_i}\sum_{y \in \omega_i} y = \frac{1}{N_i}\sum_{x \in \omega_i} w^T x = w^T \mu_i \quad (1)$$

6. Choose the distance between the projected means using Eq.2 [34..39]:

$$J(w) = |\tilde{\mu}_1 - \tilde{\mu}_2| = |w^T(\mu_1 - \mu_2)| \quad (2)$$

B. Discrete Fourier Transform (DFT)

The input samples to DFT are real numbers and the output coefficients are complex. The combination of sinusoids obtained using DFT is periodic with that same period [48]. If f(m, n) is a function of two discrete spatial variables m and n, a two-dimensional Fourier transform of f(m, n) by Eq.3 [49]:

$$F(\omega_1, \omega_2) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} f(m,n) e^{-j\omega_1 m} e^{-j\omega_2 n} \quad (3)$$

w1 and w2: frequency variables and their units are radians per sample.

F(w1, w2): frequency-domain representation function of f(m,n) that is periodic in w1 and w2, with period 2π.

Because of the periodicity, only range is displayed -π <= w1, w2 <= π.

F(0,0) is called constant component of Fourier transform because F(0,0) is the sum of all the values of f(m,n).

Working with Fourier transform on a computer involves DFT for two reasons: the input/output of DFT are discrete; and there is a fast algorithm for computing DFT known fast Fourier transform (FFT).

The DFT is defined for a discrete function f(m,n) that is nonzero only over finite region 0 <= m <= M-1 and 0 <= n <= N-1 . The two-dimensional M-by-N DFT and inverse M-by-N DFT relationships are given by Eq.4 and Eq.5

$$F(p,q) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m,n) e^{-j(2\pi/M)pm} e^{-j(2\pi/N)qn} \qquad \begin{matrix} p = 0, 1, \ldots, M-1 \\ q = 0, 1, \ldots, N-1 \end{matrix} \quad (4)$$

$$f(m,n) = \frac{1}{MN} \sum_{p=0}^{M-1} \sum_{q=0}^{N-1} F(p,q) e^{j(2\pi/M)pm} e^{j(2\pi/N)qn} \qquad \begin{matrix} m = 0, 1, \ldots, M-1 \\ n = 0, 1, \ldots, N-1 \end{matrix} \quad (5)$$

The values F(p, q) are called DFT coefficients of f(m,n) [49]

C. Discrete Cosine Transform (DCT)

DCT transforms input signal or image from spatial domain to frequency domain. DCT uses cosine base functions. DCT of N×M image f(x, y) is defined by Eq.6 [40-47]:

$$F(u,v) = \alpha(u)\alpha(v)\sum_{x=0}^{N-1}\sum_{y=0}^{M-1} .\cos[\frac{\pi.u}{2.N}(2x+1)]\cos[\frac{\pi.u}{2.M}(2y+1)]f(x,y) \quad (6)$$

Where f (x, y): intensity of pixel in row x and column y,
u = 0,1, …, N-1,
v =0,1,…, M-1,
α(u), α (v) : functions are defined as Eq.7 [40-47]:

$$\alpha(u), \alpha(v) = \begin{cases} \sqrt{\frac{1}{N}} & for \quad u,v = 0 \\ \sqrt{\frac{2}{N}} & for \quad u,v \neq 0 \end{cases} \quad (7)$$

Much of signal energy lies at low frequencies for most images. These are relocated to upper-left corner of DCT array. Lower-right values of DCT array represent higher frequencies and turn out to be small to be removed with little visible distortion especially when u and v approach respectively the sub-image width and height. This means that the DCT is an effective tool that can pack the most effective features of input image into the fewest coefficients. The recognition rate can be effected by number of DCT coefficients [40-47].

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III. PRACTICAL SWARM OPTIMIZATION

PSO algorithm is easy to implement, converge rapidly and can be applied on large number of samples. PSO is one of the swarm intelligence methods that explore global optimal solution. PSO is proposed by Kennedy and Eberhart in 1995 [17] and it is based on social behavior of birds flocking. It uses swarm of particles as the individuals in the population for searching through solution space. PSO has many benefits: flexibility; self-organized having no clear leader can use post memory; swarming nature; colonial life. The PSO can be summarized by the following points [16-26]:

- The swarm is population and it is a set of vectors.
- Each solution is implemented as a particle that represents one individual of a population.
- A particle can be regarded as a point of N-dimension solution space and has a speed.
- Each particle has a fitness function associated with it. Each particle adjusts and evaluate their position and move closer to optimal point. Particles compare themselves to their neighbors and imitate the best of that neighbor.
- Eq.8 is used to compute new velocity of each particle:
  Vi(t+1)=W×Vi(t) + C1×rand × (Pbest(t)-Xi(t))+ C2 × rand × (Gbest(t)-Xi(t))...(8)

  Where, V[]: particle velocity of particle,
  Xi: ith particle of swarm
  W: weight (random number between 0 and 1).
  C1, C2 : speeding factors (with value 2).
  Pbest: best value of particle i.
  Gbest: best value that one of swarm particle reach it.
  Lbest: best value that particle in a local swarm reach it.

  From Eq.8, the new velocity vi(t+1) is affected by: Pbest, Gbest and Vi(t): earlier velocity of ith particle X in time t.

- Eq.9 is used to compute new fitness value of each particle in swarm:
  Xi(t+1)=Xi(t) + Vi(t+1) ………………………… (9)

  The particle will change its value according to its new velocity (vi(t+1)) [16-26].

IV. RESEARCH METHODOLOGY

A gait recognition system based on PSO is suggested in this work. Three feature extraction methods: LDA, DFT and DCT were used separately to reduce dimensionality and extract features from images before applying to PSO. MatLab2013 is used to implement the main steps for PSO for training/testing gait recognition system. This research depends on a database taken from CASIA [55] database with different views that have different silhouette in person's height and width. The Institute of Automation, Chinese Academy of Sciences (CASIA) provide CASIA Gait Database to gait recognition to promote researches. The DataBase of the suggested system includes 9000 (240×352) images of 15 persons which selected from CASIA database. Each person with 50 images (states) for 4 cases for three angles (0, 45 and 90). At the end the selected database includes: 15 person × 3 angles × 4 cases × 50 states =9000 images.

A. PSO Training Process of Gait Recognition

The training part of the gait recognition system can be summarized by the following steps:

1. Read 50 (240×352) images for each one of the 4 states for each one of the three angles (0, 45 and 90).
2. The logical OR gate will be applied on each 50 images to produce one average image for each case of the 4 cases. This is applied for each angle. The total number of images resulted from this process are: 15 × 3 × 4 × 1= 180 images for 15 persons. Fig 1 shows image of person 1 after applying OR on 50 images of gait of person1 for angle 90°. Fig 2 shows image of person 1 after applying OR on 50 images of gait of person1 for angle 0°. Whereas Fig 3 shows image of person 2 after applying OR on 50 images of gait of person1 for angle 45°.
3. Resize each image from dimension 240×352 to dimension 190×100. This is done to produce a dataset with the same position of the person in the middle of each frame and same size in whole image sequence. Three stage preprocessing will be performed: extract rectangle including person without extra black pixels and obtain height and width of the person; sequence is calculated and each frame is converted to biggest height and width; and finally, move head of each frame in a fixed point.
4. Take small block (70×70, 60×60, 40×40 or 20×20) from each (190×100) image. Different dimension will be used in this research.
5. Convert each sub image block from two dimensional array to one dimensional array.
6. LDA, DFT or DCT will be used to extract person properties.
7. PSO is used for each one of 180 feature vectors (generated either using LDA DFT or DCT). PSO can be summarized by the following steps:
   Step1: Initialize PSO parameters as follows: PSO swarm size equal either 40, 30 or 20; C1 with 2; C2 with 2; Swarm weight equal 0.5 and number of iterations equal 100 or 150.

   Step 2: Initialize position and velocity of each sample. Initialize lbest and gbest.

   Step3: Calculate fitness function of each sample.

   Step4: Calculate optimal value of particle swarm (pbest) and optimum value of group (gbest) according to comparison between the current value of particle and the pbest and gbest.

   Step5: Calculate the new speed of practical using Eq.8.

   Step6: Compute new position of particle using Eq.9.

   Step7: Repeat steps 3 to 6 while there are more iterations to be executed.

   Step8: Store features sub set which are represented by vector with length equal to population size in sub features database.

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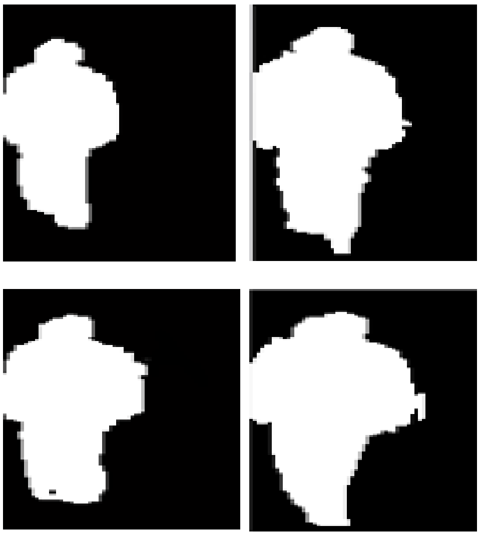

Fig 1: Image of person 1 after applying OR on 50 images of gait of person1 for angle 90°

Fig 2: Image of person 1 after applying OR on 50 images of gait of person1 for angle 0°

B. PSO Testing Process of Gait Recognition

The testing part of the system can be summarized as follows:

1. Input 50 images with dimension 240×352 pixels for one case for one angle for one person to be identified.
2. Apply OR on the 50 images.
3. Resize the resulted image (240×352) to (190×100).
4. Future extraction LDA/DFT/DCT on one block of image.
5. PSO for features subset.
6. Compare resulted features with features in DataBase. The person is identified if the features Matched Features.

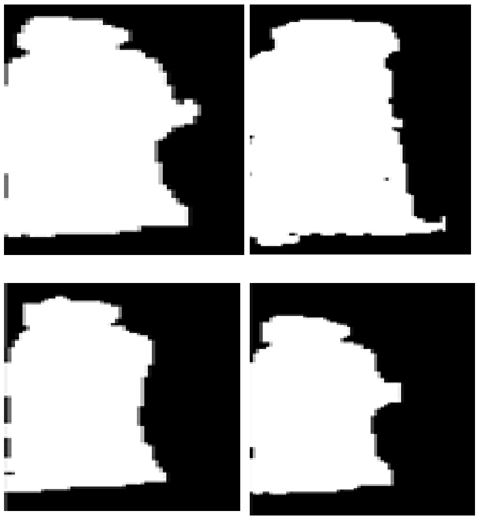

Fig 3: Image of person 2 after applying OR on 50 images of gait of person2 for angle45°

V. EXPERIMENTAL RESULTS

In this research, MATHLAB 2013 was used to implement the suggested gait recognition system based on PSO with LDA/DFT/DCT. Many experiments were conducted for the gait recognition system based on CASIA Gait Database [55]. The DataBase includes images (with 240×352 dimension) of 15 persons each person with 3 angles (0, 45 and 90), each angle with 4 cases and 50 images for each case. Finally, the database includes 9000 images. Recognition ratio, MSE, PSNR and required time were used to measure the performance of the suggested system.

In the first three experiments, the feature extraction process is achieved using either LDA, DCT and DFT respectively. Then the PSO is executed with swarm size equal 40 and number of iterations equal 100. We tested the PSO based either on LDA, DFT or DCT with various size of feature vectors (70×70, 60×60, 40×40 and 20×20). Table I shows the recognition rate, MSE, PSNR and required time when using LDA/DCT/DFT as feature extraction with different dimension of sub image.

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Table I: PSO based LDA/DCT/DFT results (Swarm size N=40, No. of Iterations=100)

	LDA				DCT				DFT			
Sub image	Reco. rate	MSE	PSNR	Time	Reco. rate	MSE	PS-NR	Time	Reco. rate	MSE	PSNR	Time
70×70	97%	0.0027	38	94	96%	0.0088	35	137	96%	0.0076	36	135
60×60	94%	0.0092	33	74	92%	0.0121	32	98	93%	0.0115	34	97
40×40	91%	0.0232	30	63	89%	0.0187	29	79	90%	0.0171	30	81
20×20	89%	0.0645	29	51	85%	0.0211	27	67	87%	0.0195	29	69

We can note from Table I that best results including highest recognition rate, lowest MSE, lowest time and highest PSNR were obtained when selecting feature dimension equal 70×70. Also from these experiments, we can note that the results obtained from using LDA for feature extraction is better than the results obtained from using DFT and DCT as feature extraction.

Another 3 experiments were conducted for PSO either with LDA, DCT or DFT based on swarm size equal 40 and 150 number of iterations. At the same time, we determined different sub image dimension (70×70, 60×60, 40×40 or 20×20). Table II shows results of PSO based LDA/DCT/DFT with swarm size equal 40 and 150 number of iterations.

Table II: PSO based LDA/DCT/DFT results (swarm size N=40, No. of Iterations=150)

Subset image	LDA			DCT			DFT		
	Reco.rate	MSE	PSNR	Reco.rate	MSE	PSNR	Reco.rate	MSE	PSNR
70*70	96%	0.0096	37	95%	0.0089	34	95%	0.0073	35
60*60	93%	0.0098	32	91%	0.0134	30	91%	0.0134	31
40*40	91%	0.0245	30	87%	0.0178	28	89%	0.0164	29
20*20	88%	0.0678	28	84%	0.0256	26	86%	0.0243	26

Other three experiments were based on PSO based LDA/DCT/DFT with swarm size equal 30, number of iterations equal 100, with different size of sub image dimension (70×70, 60×60, 40×40 or 20×20).

Table III shows results of PSO based LDA/DCT with Swarm size N=30 and number of Iteration=100.

Table III: PSO based LDA/DCT/DFT results (swarm size N=30, No. of Iterations=100)

Subset image	LDA			DCT			DFT		
	Reco.rate	MSE	PSNR	Reco.rate	MSE	PSNR	Reco.rate	MSE	PSNR
70*70	96%	0.0031	37	95%	0.0091	34	95%	0.0081	35
60*60	93%	0.0094	32	91%	0.0125	31	92%	0.0117	31
40*40	90%	0.0235	30	88%	0.0189	28	89%	0.0171	29
20*20	88%	0.0647	28	84%	0.0217	27	86%	0.0204	27

Other experiments were based on PSO based LDA/DCT/DFT with swarm size equal 30, number of iterations equal 150, with different size of sub image dimension (70×70, 60×60, 40×40 or 20×20).

Table IV shows results of PSO based LDA/DCT/DFT with swarm size equal 30 and 150 number of Iterations.

Table IV: PSO based LDA/DCT/DFT results (swarm size N=30, No. of Iterations=150)

Subset image	LDA			DCT			DFT		
	Reco.rate	MSE	PSNR	Reco.rate	MSE	PSNR	Reco.rate	MSE	PSNR
70*70	93%	0.0055	33	91%	0.0119	32	92%	0.0112	32
60*60	90%	0.0122	30	87%	0.0178	28	88%	0.0164	29
40*40	87%	0.0276	26	86%	0.0220	27	86%	0.0212	27
20*20	84%	0.0676	25	84%	0.0276	26	84%	0.0262	26

Other experiments were based on PSO based LDA/DCT/DFT with swarm size equal 20, number of iterations equal 150, with different size of sub image dimension (70×70, 60×60, 40×40 or 20×20).

Table V shows results of PSO based LDA/DCT/DFT with swarm size equal 20 and 150 number of iterations.

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Table V: PSO based LDA/DCT/DFT results (swarm size N=20, No. of Iterations=150)

Subset image	LDA			DCT			DFT		
	Reco.rate	MSE	PSNR	Reco.rate	MSE	PSNR	Reco. rate	MSE	PSNR
70*70	89%	0.0089	30	90%	0.0122	30	90%	0.0109	29
60*60	88%	0.0188	28	86%	0.0187	26	85%	0.0171	25
40*40	82%	0.0295	25	84%	0.0224	25	83%	0.0214	24
20*20	82%	0.0711	22	82%	0.0287	24	80%	0.0272	23

From Table III, Table VI, Table V, we can note that the swarm size can affect the overall results (recognition rate, MSE, PSNR and required time). The best results of recognition rate were obtained when selecting swarm size equal 40 with 100 iterations. Also the dimension of the sub image can affect the recognition rate of the system. Best recognition rates for all experiments were obtained when determining sub image dimension equal 70×70. This is because the big sub image dimension will take more features of the image. Whereas the results related to recognition rate are low when determining sub image dimension equal 20×20 because small features of image will be taken.

A. LDA vs. DCT and DCT

According to the results of the first three experiments that are shown in table I, we can examine the differences between LDA, DFT and DCT. Each experiment with different image block size (70×70, 60×60, 40×40 or 20×20) but with 100 number of iterations and swarm size equal 40. Fig 4 shows the recognition rate of these experiments.

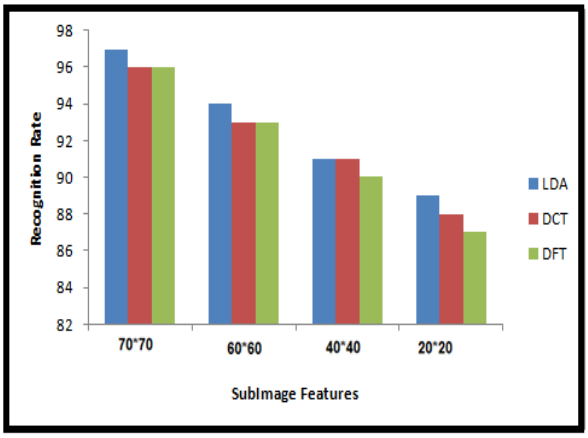

Fig 4: Recognition rates when using LDA/DFT/DCT

We can note from Fig 4 that recognition rates of gait recognition system using PSO based LDA are better than the recognition rates when using DFT and DCT. Fig 5 shows the MSE of these experiments.

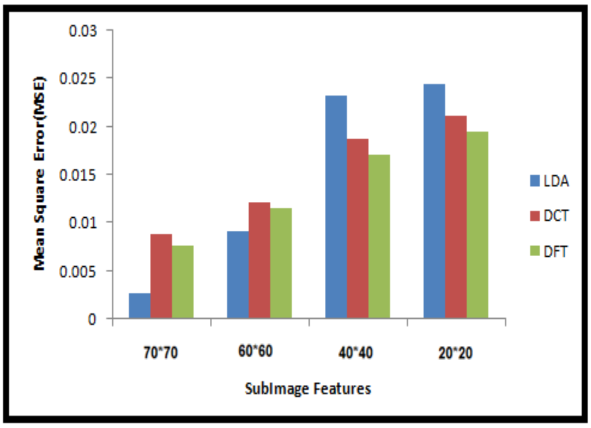

Fig 5: MSE when using LDA/DFT/DCT

We can note from Fig 5 that the lowest values of MSE were obtained when using LDA. Fig 6 shows the PSNR of the gait recognition system based on PSO with LDA, DFT and DCT respectively.

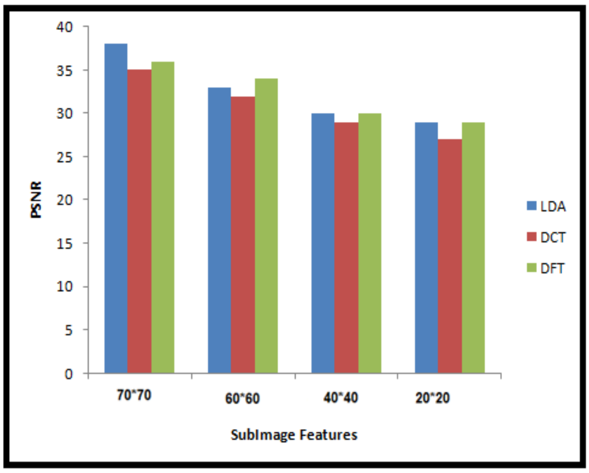

Fig 6: PSNR when using LDA/DFT/DCT

We can note from Fig.6 that the highest values of PSNR were obtained when using LDA. Finally, Fig 7 shows the differences in training time for gait recognition when using LDA, DFT and DCT.

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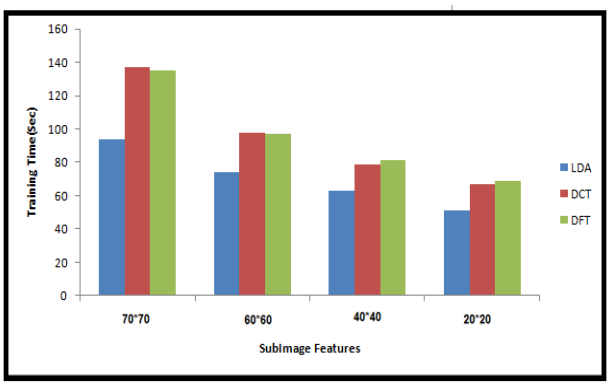

Fig 7: Training time when using LDA and DCT

We can note from Fig.7 that the lowest computation times were obtained when using LDA.

VI. CONCLUSION

This work includes presentation of gait recognition system based on PSO. Three feature extraction methods (LDA, DFT and DCT) were used separately to reduce the dimensionality of the input image. MATLAB 2013 software was used to implement the gait recognition system. The DataBase of the suggested gait recognition program includes 9000 images (each of dimension 240×352 pixels) of 15 persons that selected from CASIA database [55] with different angles (0, 45 and 90), cases (4 cases) and states (50 state for each person).

Many experiments were conducted to determine the performance of gait recognition system based on PSO. The experiments were based on LDA, DFT and DCT separately. This is done to examine the feature extraction algorithm that improve the gait recognition performance. Also, these experiments were executed with different: swarm size, number of iterations and feature block dimension.

The experimental results showed that the best values of recognition rate, MSE and PSNR were obtained when increasing the feature block size to dimension 70×70. Also best results were obtained when increasing the swarm size to 40 and decrease number of iterations to 100. The recognition rate reached 97%, MSE reached 0.0027and finally PSNR reached 38% when adopting LDA algorithm. This means that best results were obtained when using LDA in comparison with DFT and DCT. And also the results obtained from DFT are better than the results obtained from using DCT. The time required for executing the LDA is lowest than the time required for executing DFT and DCT. DCT require more time than LDA and DFT.

As a future work, the gait recognition results of PSO algorithm will be compared with the results of gait recognition system which based on genetic algorithm.

REFERENCES

1. Sruthy Sebastian, Activity Based Person Identification Using Particle Swarm Optimization Algorithm, International Journal of Computer Science and Mobile Computing, Vol.2, Issue.7, pp:1-6, Jul2013.
2. A. K. Jain, A. Ross, S. Prabhakar, "An Introduction to Biometric Recognition", IEEE Trans. on Circuits and Systems for Video Technology, Vol.14, No.1, pp 4-19, Jan2004.
3. Gajanan P. K., et al. Human Computer Interpreting with Biometric Recognition System, International Journal of Advanced Research in Computer Science and Software Engineering, Vol.2, Issue.12, pp:140-147, Dec2012.
4. Adam Świtoński, et al. Human Identification Based on the Reduced Kinematic Data of the Gait, 7th International Symposium on Image and Signal Processing and Analysis (ISPA), IEEE, pp:650–655, Dubrovnik,4-6 Sep2011.
5. M.Tistarelli, J.Bigun, and E.Grosso, Biometric Gait Recognition, Biometrics School 2003, LNCS 3161, pp: 19–42, 2005.
6. Liang Wang, et al. Silhouette Analysis-Based Gait Recognition for Human Identification, IEEE Transactions On Pattern Analysis And Machine Intelligence, Vol.25, No.12, pp:1-14, Dec2003.
7. Liang Wang, , et al, Fusion of Static and Dynamic Body Biometrics for Gait Recognition, Proceedings of the Ninth IEEE International Conference on Computer Vision (ICCV 2003), Vol.2.
8. Chiraz BenAbdelkader, et al. EigenGait: Motion-based Recognition of People using Image Self-Similarity, Lecture Notes in Computer Science Volume 2091, pp:284-294, 2001.
9. Payam Saisan and Swarup Medasani and Yuri Owechko, Multi-View Classifier Swarms for Pedestrian Detection and Tracking, IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR Workshops, San Diego, CA, USA, 25-25Jun2005.
10. Qiong C., Bo F., and Hui C., Gait Recognition Based on PCA and LDA, Proceedings of the Second Symposium International Computer Science and Computational Technology(ISCSCT '09), Huangshan, P. R. China, pp:124-127, 26-28Dec2009.
11. Ra´ul M. and Tao Xiang, Gait Recognition by Ranking, A. Fitzgibbon et al. (Eds.): ECCV 2012, Part I, LNCS 7572, pp:328–341, Springer-Verlag Berlin Heidelberg,2012.
12. Mohamed Rafi, et al. A Model Based Approach for Gait Recognition System, International Journal of Soft Computing and Engineering (IJSCE) ISSN: 2231-2307, Vol.3, Issue.5, pp:223-228, Nov 2013
13. Bogdan Kwolek, et al. 3D Gait Recognition Using Spatio-Temporal Motion Descriptors, DOI: 10.1007/978-3-319-05458-2_61 In book: Intelligent Information and Database Systems, Publisher: Springer International Publishing, Editors: Nguyen, NgocThanh and Attachoo, Boonwat and Trawiński, Bogdan and Somboonviwat, Kulwadee, pp.595-604, 2014.
14. Rong Z., Christian V. and Dimitris M., Human Gait Recognition, Conference on Computer Vision and Pattern Recognition Workshop, 27-02Jun2004. CVPRW '04.
15. Adam S., Andrzej P., Konrad W., Human Identification Based on Gait Paths, book chapter: Advanced Concepts for Intelligent Vision Systems, 13th International Conference, ACIVS 2011, Ghent, Belgium, August 22-25, 2011. Proceedings DOI: 10.1007/978-3-642-23687-7_48, pp 531-542, 2011.
16. Qinghai Bai, Analysis of Particle Swarm Optimization Algorithm, Computer and Information Science, Vol.3, No.1, 2010.
17. Kennedy, J. and Eberhart, R. (1995), Particle swarm optimization, Proceedings of IEEE International Conference on Neural Networks, Perth, WA, 1942-1948.
18. H. Kuo, J. Chang and C. Liu, Particle Swarm Optimization For Global Optimization Problems, Journal of Marine Science and Technology, Vol. 14, No. 3, pp:170-181, 2006.
19. Dian P.R., Siti M.S. and Siti S.Y., Particle Swarm Optimization: Technique, System and Challenges, International Journal of Computer Applications, Vol.14, No.1, pp:19-27, Jan2011
20. Satyobroto Talukder, Mathematical Modelling and Applications of Particle Swarm Optimization, Master's Thesis, Mathematical Modelling and Simulation, School of Engineering at Blekinge Institute of Technology,Master of Science, Feb 2011.
21. Voratas K., Comparison of Three Evolutionary Algorithms: GA, PSO, and DE, Industrial Engineering & Management Systems, Vol.11, No.3, pp.215-223, Sep2012.
22. Daniel Bratton and James Kennedy, Defining a Standard for Particle Swarm Optimization, Proceedings of the 2007 IEEE Swarm Intelligence Symposium (SIS 2007).
23. Davoud S. and Ellips M., Particle Swarm Optimization Methods, Taxonomy and Applications, International Journal of Computer Theory and Engineering, Vol. 1, No. 5, pp: 486-502, Dec 2009.
24. M. Peyvandi, M. Zafarani and E. Nasr, Comparison of Particle Swarm Optimization and the Genetic Algorithm in the Improvement of Power System Stability by an SSSC-based Controller, Journal of Electrical Engineering & Technology Vol. 6, No. 2, pp:182-191, 2011.
25. Bijayalaxmi Panda, Soumya Sahoo, Sovan Kumar Patnaik, A Comparative Study of Hard and Soft Clustering Using Swarm Optimization, International Journal of Scientific & Engineering Research, Vol.4, Issue.10, pp:785-790, Oct-2013 ISSN 2229-5518

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26. Rania Hassan, Babak Cohanim, Olivier de Weck, A Copmarison Of Particle Swarm Optimization And The Genetic Algorithm, American Institute of Aeronautics and Astronautics, 46th Aiaa/Asme/Asce/Ahs/Asc Structures, Structural Dynamics And Materials Conference, 2005.
27. R. M. Ramadan and R. F. AbdelKader, Face Recognition Using Particle Swarm Optimization-Based Selected Features, International Journal of Signal Processing, Image Processing and Pattern Recognition, Vol.2, No.2, pp:51-66, Jun2009.
28. P.V. Shinde, B.L. Gunjal and R. G. Ghule, Face Recognition Using Particle Swarm Optimization, Emerging Trends in Computer Science and Information Technology -2012(ETCSIT2012) Proceedings published in International Journal of Computer Applications® (IJCA), pp:11-13.
29. M. Arunkumar And S. Valarmathy, Palmprint And Face Based Multimodal Recognition Using Pso Dependent Feature Level Fusion, Journal of Theoretical and Applied Information Technology,Vol.57, No.3, pp:337-346, 30th November 2013.
30. K. Krishneswari and S. Arumugam, Intramodal Feature Fusion Based On Pso For Palmprint Authentication, Ictact Journal On Image And Video Processing, May 2012, Vol.2, Issue: 04, pp:435-440.
31. Ola M. Aly, et al., A Multimodal Biometric Recognition system using feature fusion based on PSO, International Journal of Advanced Research in Computer and Communication Engineering, Vol. 2, Issue.11, pp: 4336-4343, Nov2013.
32. Ola M. Aly, et al., An Adaptive Multimodal Biometrics System using PSO, International Journal of Advanced Computer Science and Applications, Vol. 4, No.7, pp:158-165,2013
33. S. Ivekovic, E. Trucco and Y. R. Petillot, Human Body Pose Estimation With Particle Swarm Optimisation, Evolutionary Computation, Vol.16, No.4, pp: 509-528.
34. Ricardo Gutierrez-Osuna, CSCE 666 Pattern Analysis, L10: Linear discriminants analysis, CSE@TAMU.
35. C.R. Rao, Linear Statistical Inference and Its Applications, second ed.Wiley Interscience, 2002.
36. K. Fukunaga, Introduction to Statistical Pattern Recognition, 2nd ed San Diego, CA: Academic, 1990.
37. T. Hastie, R. Tibshirani, and J. H. Friedman, The Elements of Statistical Learning: Data Mining, Inference, and Prediction. New York: Springer-Verlag, 2001.
38. A. M. Martinez and M. Zhu, “Where are linear feature extraction methods applicable?,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 27, no. 12, pp. 1934–1944, Dec. 2005.
39. Shuiwang Ji and Jieping Ye, Generalized Linear Discriminant Analysis: A Unified Framework and Efficient Model Selection, IEEE Transactions On Neural Networks, Vol.19, No.10, pp:1768-1782. Oct2008.
40. M. Ahmad, T. Natarajan and K. R. Rao, Discrete Cosine Transform, IEEE Trans. Computers, 1974, pp:90-94.
41. Aman R. C., Pallavi P. V. and M. M. Roja, Face Recognition Using Discrete Cosine Transform for Global and Local Features, Proceedings of the 2011 International Conference on Recent Advancements in Electrical, Electronics and Control Engineering IEEE Xplore:CFP1153R-ART; ISBN: 978-1-4577-2149-6
42. Ziad M. Hafed and Martin D. Levine, Face Recognition Using the Discrete Cosine Transform, International Journal of Computer Vision , Vol.43, No.3, pp:167–188, 2001 Kluwer Academic Publishers. Manufactured in The Netherlands.
43. C. Podilchuk and X. Zhang, “Face Recognition Using DCT-Based Feature Vectors,” Proc. IEEE International Conference on Acoustics, Speech and Signal Processing, vol. 4, pp. 2144-2147, May 1996.
44. Z. Yankun and L. Chongqing, “Efficient Face Recognition Method based on DCT and LDA,” Journal of Systems Engineering and Electronics, vol. 15, no. 2, pp. 211-216, 2004.
45. F. M. Matos, L. V. Batista, and J. Poel, “Face Recognition Using DCT Coefficients Selection,” Proc. of the 2008 ACM Symposium on Applied Computing, (SAC’08),pp. 1753-1757, March 2008.
46. Z. Pan and H. Bolouri, “High Speed Face Recognition Based on Discrete Cosine Transform and Neural Networks,” Technical Report, Science and Technology Research Center (STRC), University of Hertfordshire.
47. Virendra P. Vishwakarma, Sujata Pandey Member IEEE, and M. N. Gupta , A Novel Approach for Face Recognition Using DCT Coefficients Re-scaling for Illumination Normalization, 15th International Conference on Advanced Computing and Communications, IEEE Computer Sociaety, pp:535-539.
48. Signal Processing Toolbox™ User's Guide, R2015a, The MathWorks, Inc., 1988–2015.
49. Image Processing Toolbox For Use with MATLAB, User’s Guide Version 2, The MathWorks, Inc. 1993 – 1998.
50. Kazuyuki Miyazawa, et al. A Phase-Based Iris Recognition Algorithm. D. Zhang and A.K. Jain (Eds.): ICB 2006, LNCS 3832, pp. 356–365, 2005, Springer-Verlag Berlin Heidelberg 2005.
51. Poulami Das, et al. Person Identification through IRIS Recognition, International Journal of Security and its Applications Vol. 3, No. 1, January, 2009, pp:129-148.
52. Jaydeep K., Nilesh G. Pardeshi and Vikas N., Improved Iris Recognition using Discrete Fourier Transform, International Journal of Computer Applications (0975 – 8887) International Conference on Recent Trends in engineering & Technology - 2013(ICRTET'2013), pp:33-38.
53. Ahmed Mostayed, et al. Abnormal Gait Detection Using Discrete Fourier Transform, International Journal of Hybrid Information Technology Vol.3, No.2, April, 2010, pp:1-8.
54. K Manikantan and S Ramachandran, DFT domain Feature Extraction using Edge-based Scale Normalization for Enhanced Face Recognition, Journal of Advanced Computer Science and Technology, Vol.1, No.3, 2012, pp:134-166, Science Publishing Corporation,
55. CASIA Gait Database, http:// www.sinobiometrics.com, 2006. CASIA Gait Database collected by Institute of Automation, Chinese Academy of Sciences" and a citation to "CASIA Gait Database.

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