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A Comparison of Facial Recognition Techniques

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Abstract. In this paper, facial recognition has been widely studied due to its importance in many applications in the civilian and military domains. Although this computer vision problem was initially challenging due to the dynamic nature of the human face and the different poses it can take, however, the research conducted over the last two decades made huge advances with many algorithms reporting high accuracy in the published literature. However, this accuracy is usually reduced in real-life usage especially in the presence of different types of noise. In this paper, six different facial recognition algorithms are evaluated and compared, namely, principle component analysis (PCA), two-dimensional PCA (2D-PCA), linear discriminant analysis (LDA), discrete cosine transform (DCT), support Vector Machines (SVM) and independent component analysis (ICA). The effect of the presence of Gaussian and salt and Pepper noises are also considered during the evaluation of these algorithms. The results show that the best performance was obtained using the DCT algorithm with 92% dominant eigenvalues and 95.25 % accuracy which makes it the best choice under different noise conditions.

Keywords: Face Recognition, PCA, LDA, SVM, ICA, DCT.

1 Introduction

Face recognition is very important and vital tools for verification or identification purposes for a research related to the applications in law enforcement and in commercial. For example, identifying the suspects at airports based on what are called black-listed persons. The identification process should be as accurate and fast as possible. In many cases, the black-list or the dataset contains a large number of images, which will negatively affect the speed and the accuracy of the algorithm. Several algorithms have been proposed to solve the speed and accuracy problem such as principle component analysis (PCA) [11], [12], [4], two-dimensional PCA (2D-PCA) [3], and discrete cosine transforms PCA (DCT-PCA) [2]. These algorithms allow a high-dimensional space to be represented in a low-dimensional one. The PCA algorithm extracts the main features (eyes, nose, and mouth) for the covariance matrix of the dataset by employing its eigenvalues after converting the covariance matrix into a vector. The 2D-PCA is a modifying version of PCA which doesn't converting the covariance matrix into a vector, in order to preserve the positions of the features.
There are two available important facial recognition methods, appearance- and model-based algorithms. The former represents a face by defining several raw intensity and

high-dimensional vector images. To derive a feature defined space from the image distribution, statistical techniques should be used. After that, the sample image is compared to the training set. Moreover, the appearance methods can be categorized as linear or nonlinear methods. For example, the linear appearance-based methods execute a linear dimension reduction. And the face vectors are projected to the basis vectors. The projection coefficients are used for each face image and approaches that included PCA, LDA, and Independent Component Analysis (ICA) [15], [16].

Finally, the DCT-PCA applies the same idea of the 2D-PCA in the transform domain instead of the spatial domain. Principal component analysis (PCA) [11] ensure the minimum mean square error as the basis of subspace to gain linearly independent vectors. It is considered one of the algorithms for classical dimensionality reduction. However, if the PCA is used to process images, the images must be transformed into vectors firstly where they contain m rows and n columns pixels. To overcome the problem of the dimensionality, the procedure should gain fewer samples. In this case, the gained dimensionalities of the subspace are lower compared to a relatively bigger error in the reconstruction. Jian et al. proposed an improvement for PCA called the two-dimensional principal component analysis (2DPCA) [13]. It processes the images that are made up of m rows and n columns of pixels. Therefore, using 2DPCA gains more basis of subspace and deletes the step of vectorization.

1.1 PCA and 2DPCA

Characterization of PCA Algorithm. One of the common dimensionality reduction algorithms is PCA while Discrete K-L Transformation is considered the theoretical basis. It is also called Eigenface method [3]. The algorithm is presented as follows:

- *Preprocessing of data.* Consider that we have M images, I1, I2,…..,IM as training samples and each image is constructed from m rows and n columns pixels. This is followed by transforming all images into image vectors **Γ**1,**Γ**2,…..,**Γ**M where the vector's dimensionality for each image is m*n.

- *Determining feature space.* The training samples mean values are computed first as follows:

$$\Psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma i$$

Let$\Phi i = \Gamma i - \Psi$, i= 1, 2…… M, where the matrix of covariance for all image vectors is:

$$C = \frac{1}{M}\sum_{i=1}^{M}\Phi i\Phi\ \mathbf{t_i} \tag{1}$$

These eigenvectors u i (i=1 2......d) is what we called eigenfaces in relating to the largest d eigenvalues of C.

- *Recognition*. All training images' vector representations $\boldsymbol{\Omega i}$= [u1 u2 ……ud]T $\boldsymbol{\Phi i}$ can be gained by projecting them to feature subspace in the lower dimensionality space. Then, for each test image vector Γtest , its projection can be gained as **Ω**test =[u1 u2 ……….ud]T (**Γ**test – **Ψ**) in the feature subspace. In the last step, the Euclidean distance can be used $\boldsymbol{\varepsilon}$i =

$\| \boldsymbol{\Omega i} - \boldsymbol{\Omega}$test$\|2$, i=1,2,……..M for the similarity measurement among images[3]. It is worth mentioning that if the Euclidean distance is less and then the similar images are more.

Description of 2DPCA. As mentioned earlier, before using PCA algorithm, each image must be transformed into image vector. These digital images are constructed in a two-dimensional matrix that is made up of pixels. Yang et al. [13] reported 2DPCA which directly processes two-dimensional images and eliminates the vectorization step. The algorithm is described as follows:

- *Computing feature space*. The training image samples M are defined as I1, I2,……IM, and each image constructed from m rows and n columns pixels. Then, the mean value of the training samples will be computed as:

$$\boldsymbol{\Psi} = \frac{1}{M}\sum_{i=1}^{M} \mathbf{Ii}. \text{ Let } \boldsymbol{\Phi i} = \mathbf{Ii} - \boldsymbol{\Psi}$$

, then the covariance matrix of all images is:

$$\mathbf{C} = \frac{1}{\mathbf{M}}\sum_{i=1}^{M} \boldsymbol{\Phi}_i^{\mathbf{T}} \ \boldsymbol{\Phi}_i \tag{2}$$

The eigenvectors *ui* (i =1 2 ... d) corresponding to the largest *d* eigenvalues of *C* are the basis of feature subspace. It is worth mentioning that $\boldsymbol{\Psi}$ and $\boldsymbol{\Phi}$ is both 2D matrices, but not they are image vectors in PCA algorithm [3].

- *Recognition.* At beginning step, each training image's lower dimensionality gains its representation $\boldsymbol{\Omega}\mathbf{i} = [\boldsymbol{\Omega}_{\mathbf{i},\mathbf{1}}, \boldsymbol{\Omega}_{\mathbf{i},\mathbf{2}} \ldots\ldots \boldsymbol{\Omega}_{\mathbf{i},\mathbf{d}}] = \boldsymbol{\Phi}_{\mathbf{i}}$[u1 u2……ud] by projecting it to feature subspace, where $\boldsymbol{\Omega}_{\mathbf{i},\mathbf{j}}$, j=1, 2…d is the jth column of$\boldsymbol{\Omega}_{\mathbf{i}}$ In the second step, for each test image Itest, we get its projection $\boldsymbol{\Omega}_{\mathbf{test}}$= [$\boldsymbol{\Omega}_{\mathbf{test},\mathbf{1}}$ $\boldsymbol{\Omega}_{\mathbf{test},\mathbf{2}}$…$\boldsymbol{\Omega}_{\mathbf{test},\mathbf{d}}$] = (Itest –$\boldsymbol{\Psi}$)[u1 u2….ud] in the feature subspace, where $\boldsymbol{\Omega}_{\mathbf{test},\mathbf{j}}$, j=1,2,…………,d is the jth column of $\boldsymbol{\Omega}_{\mathbf{test}}$. The last step the definition of similarity measurement is represented as follows:

$$\boldsymbol{\varepsilon}_{\mathbf{i}} = \sum_{k=1}^{d} \| \ \boldsymbol{\Omega}_{\mathbf{i},\mathbf{k}} - \boldsymbol{\Omega}_{\mathbf{test},\mathbf{k}} \ \|\mathbf{2} \tag{3}$$

The lower the value of $\boldsymbol{\varepsilon}_{\mathbf{i}}$ is, the more similar the images are.

1.2 DCT

The discrete cosine transform (DCT) is considered as an approach to extracts important features for face recognition. In this section, DCT technique are proposed and discussed. The DCT extraction involves two steps. In the first step, the DCT coefficients are obtained by applying the DCT to the entire image [2]. This is followed by selecting some of the coefficients to form feature vectors. It should be mentioned that the DCT dimension coefficient matrix is the same as the input image. Moreover, the DCT does not decrease data dimension; thus, most signal information is compressed in a small percent of coefficients [2].

DCT and coefficients selection:

If we consider an *M*N* image, where each image corresponds to a 2D matrix, the DCT coefficients are represented in the following equations:

$$\mathbf{F(u,v)}=\frac{\mathbf{1}}{\sqrt{MN}}x(u)x(v)\sum_{X=0}^{M=1}\sum_{y=0}^{N=1}f(x,y)\ \mathbf{X}cos\left(\frac{(2x+1)u\pi}{2M}\right)\ X\ cos\left(\frac{(2y+1)v\pi}{2N}\right) \quad (4)$$

u=0, 1,….., M v=0,1,…..,N Where α (ω) is defined by:

$$\alpha(\omega)\begin{cases}\frac{1}{\sqrt{2}}, & \omega = 0\\ 1, & otherwise\end{cases} \quad (5)$$

F(u ,v) is a 2D matrix of DCT coefficients and f(x ,y) is the image intensity function. The two implementations of the DCT are Block-based and the entire image implementations. In our work, the entire image DCT was considered to obtain the frequency coefficient matrix of the same dimension. The DCT coefficients are split into three sets (bands), namely, low-, middle-, and high-frequencies [2]. The selection of coefficients is a very important step of feature extraction. This stage of the feature extraction is an essential part of the feature extraction process and strongly influences the recognition accuracy. Moreover, Pan et al. [14] reported an approach to select the coefficients that lower the error of reconstruction.

1.3 Linear Discriminant Analysis (LDA)

The linear discriminant analysis (LDA) is an effective method that can be used as dimensionality reduction techniques including face- and speech-recognitions and multimedia information retrieval. The main focus of this technique is applying Fisher's criterion to find a projection A that increase the ratio of between-class scatter against within-class scatter (Sb and Sw, respectively). LDA produces a good illustration in which the original well separated information area will be linearly transformed into a low-dimensional feature space. It should be mentioned that in face recognition, the SW matrix will be singular. The traditional LDA cannot be resolved because of the problem of small sample size [17], [18].

In general, LDA uses to reduce dimensionality. The traditional LDA algorithm will be faced several difficulties if we consider for example a case of face recognition where an image with very high-dimensional data. For an example, if we consider a case where the face image of size 64*64, it implies a feature space of 64*64=4096 dimensions; thus, the scatter matrices become of the size of 4096*4096=16M. The biggest challenge is the computation of eigenvalues as they represented in very big matrices. The other challenge is related to the number of training images that needs to be at least 16M. [17], [18].

1.4 Support Vector Machine (SVM)

The most effective and useful techniques in face recognition classification is Support Vector Machines (SVM). The most advantage of SVM classifier over other network is that they can do higher generalization performance. But as other techniques, SVM encounters several difficulties. One of these difficulties, they cannot be applied once we defined samples by vectors as they will be missing entries. However, SVM as a classification algorithm can be implemented efficiently in this framework [19], [18].

It may be applied to the initial look space or a subspace of it obtained when applying a feature extraction technique [20], [21].

1.5 Independent Component Analysis (ICA)

In dealing with multivariate statistical information, independent component analysis (ICA) is used. This technique is for finding underlying factors or parts for multidimensional statistical information. ICA used as a face recognition system for the case of facial pictures that having face orientations with totally different illumination conditions. The ICA produces higher results compared with existing techniques reported in the literature [22], [23], [24], [19]. The most advantages of ICA and make it stands among other techniques is that its component is formed from both statistically autonomous and non-Gaussian [22]. In the work of Aapo Hyvärinen et. al, the ICA is related to blind source separation drawback [27].

Kailash J. Karande et al, reported the use of the ICA for face recognition with massive rotation angles with poses and variations in illumination conditions was proposed in [25]. Moreover, Kyungim Baek et al, proposed a novel subspace technique for face recognition that is called a consecutive row column independent component analysis [26]. The procedure that is implemented in the ICA for every face image is first transferred this image into a vector before manipulating the independent elements.

Another work has been done by Alfalou and Brosseau where they proposed a new technique for the face recognition that combined both the innovative component analysis model with the optical correlation technique [28]. The ICA technique had attracted a great interest in investigating a linear transformation that used to express a collection of random variables as linear combinations of statistically independent supply variables [29].

2 Literature Review

Dabbaghchian et al. [2] studied the discrete cosine transform (DCT) as a powerful approach to extract important features for face recognition. The authors used discriminant coefficients (DCs) when applying DCT to construct feature vectors for the entire face images in discrimination power analysis (DPA). Their DPA-based approach achieved the performance of both principal component analysis (PCA) and linear discriminant analysis (LDA) with less complexity then these statistical tools used for feature extraction and data representation. The authors introduced a new modification to PCA and LDA namely, DPA–PCA and DPA–LDA. This is confirmed when their simulations result of the various coefficient selection approaches applied on ORL and Yale databases. They reported that this proposed method can be implemented for any feature selection problem along with the DCT coefficients. Most importantly, Dabbaghchian and his co-authors, stated that the proposed method can operates well for the noisy image database because of its adaptive nature.

Zhang et al. [3] proposed two-dimensional (2-D) principal component analysis (PCA) based independent component analysis (ICA) algorithm for decreasing the computation complexity. They processed 2-D images directly in the preprocessing procedure. The performance of their algorithm on Yale databases was more effective compared to the conventional algorithms, such as PCA, 2DPCA and ICA.

Azeem et al. [4] wrote a survey about different methods that have been used to get rid of the problem of partial occlusion. The authors classified several methods to solve face recognition in the presence of partial occlusion. These methods are named as part-based methods that make use of PCA, local non-negative matrix Factorization (LNMF), non-negative matrix factorization (NMF), independent component analysis (ICA), linear discriminate analysis (LDA), and other variations. They provided details about the experiments and databases used in the literature to deal with the occlusion problem and the results produced after performing diverse set of analysis.

Wei and Li [5] proposed a new method for face recognition from a single image per person, which is based on the mechanism of fixations and saccades in the visual perception of human. Their method was tested on the two well-known face databases (FRGC and AR) where it performed very well when using the occlusions and expression changes. This method reported a decrease in computational cost with a good performance with the 2D warping based method.

Zhao et al. [6] introduced a new analysis of face recognition for noise images based on combinational mirror-like odd and even features. The authors studied the symmetrical and asymmetrical image information of mirror-like odd and even features in face recognition. They proposed that this combination can improve the rate of recognition to some extent under noisy condition with kernel principal component analysis (KPCA) method. Their experiments show that whenever you add the noise signals into the face images, the proper combination of the mirror-like even and odd images will keep good recognition effect. Their method could get information to identify and reach good classification results. However, due to some external factors, they recommended to adjust the proportion of each component of combinational eigenvector to increase the performance of recognition.

Archana and Venugopal [7] proposed a template-based face recognition approach and compared it with principal component analysis (PCA). They compared their experiments with the correctness or efficiency of recognition rate of PCA (70-75%) to check the performance of the systems. The observed results for their approach perform much better that PCA (more than or equal to 20%). This template-based approach can recognize the faces efficiently and invariant to change in illumination, pose, in-plane rotation, noise. Moreover, they stated that this approach can be extended to work for face recognition in multiple images not only for single images.

Budiman et al. [8] studied the face recognition using Gabor and non–negative matrix factorization (NMF) to remove noises from digital images. They proposed a proper method that can eliminate the noise in a face image that decreases the accuracy of face recognition to restore better quality of the image using smoothing (filter). They characterized three kind of noises that consist of impulse noise (salt-and-pepper), additive noise (Gaussian), and multiplicative noise (speckle). The experiment was conducted by using two face databases; they were ORL and Extended Yale B face databases. The authors reported that the mean filter is the best coping technique for Gabor and NMF face recognition methods by using ORL and Extended Yale B face databases. They used K-Nearest Neighbors (KNN) classifier as it achieved 90.83% accuracy rate compared to Cosine Similarity Measurement (CSM). Their experiments in ORL showed that some filter could handle a specific noise better than others and produce best results in handling noise and improves recognition rate.

Zaorâlek et al. [9] applied Tucker decomposition to remove noises from digital images for better recognition of face. Compared to other methods that used one image per person (PCA or singular value decomposition (SVD) to extract features from the face, they described the face by a set of images. They used three different classification methods and compare the results obtained from the classification methods. The quality of recognition can be increased using data structure like tensor and its decomposition. The accuracy of the tensor approach is compared with other well-known techniques such as support vector machine (SVM) and neural network (NN). They added Gaussian noise to images and classifiers to recognize faces belonging to current subject from foreign faces that did not belong to the subject. The results show better performance at smaller level of noise based on Tucker decomposition as it achieved stable values of accuracy and higher median accuracy in compare to SVM and NN.
A great deal of work of face recognition algorithms and recognition and various hybrid combination techniques have been developed in the last several years.

Rupesh Sutar et. al. [18] published a review of large number of face recognition algorithms including LDA, PCA, ICA, SVM, and ANN. They also reviewed various hybrid combination of ICA. This review investigates all these methods with parameters that challenges face recognition such as pose variation and facial expressions. The authors introduced a significant number of papers that cover the recent developments in the field of face recognition technologies and techniques. This review and the references there in help us to know many ways for building up the face recognition. These references also provide more detailed understanding to get the whole picture of these techniques.

3 Experiments and Discussion

The six facial algorithms are compared in this paper for different use-cases which will be discussed later in this section. Accuracy, running speed are the two factors to be measured. To perform this, the Olivetti Research Lab (ORL) [10] is used to be the dataset reference. The ORL is a popular face recognition database that contains a set of face images taken between Apr. 1992 and Apr. 1994 at Olivetti Research Lab. It is composed of 400 images of size 112 × 92. Fig.1 shows pictures for 40 persons, and for each of them, there is 10 images as shown in Fig. 1.

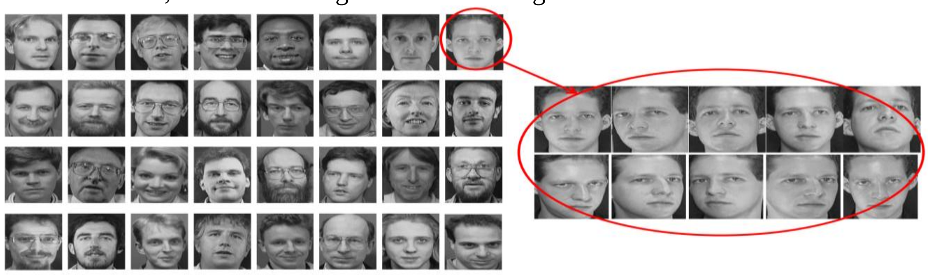

Fig. 1. ORL database have 40 persons, 10 images per each person.

3.1 We will perform two experiments to analyze the proposed facial recognition algorithms:

First experiment. Only one image per person will be used for the training. Thus, the total number of images in the training dataset is 40 images. During this experiment, we will check three different use-cases for the test images:

- A test image (different from the training images) is used with no added noise.
- The Gaussian noise is synthesized into to the test images and the result noisy images are used for testing.
- The salt and pepper noise is added to the test images similar to the Gaussian noise.

Second experiment. In the second experiment, Only Five images per person will be used for training. Thus, the total number of images in the dataset is 200 images. During this experiment, three different use-cases will be checked for the test images:

- A test image (different from the training images) is used with no added noise.
- The Gaussian noise is synthesized into to the test images and the result noisy images are used for testing.
- The salt and pepper noise is added to the test images similar to the Gaussian noise.

3.2 In each use-case, the six facial recognition algorithms are compared using the following two measures:

- Accuracy percentage (100%).
- Execution time (sec) or running speed.

3.3 Discussion

In this work, six algorithms (PCA, 2DPCA, LDA, SVM, ICA and DCT) are applied on the two experiments that mentioned earlier to study the face recognition. The result from two experiments shows that the DCT algorithm had the best accuracy compared to the other two algorithms, when the percentage of dominant eigenvalues is 92%.

The accuracy percentage in the first experiment using Gaussian- and salt and Pepper-noise were (77%) and (71%), respectively. While for the second experiment, the accuracy percentage using Gaussian- and salt and Pepper-noise were (95.25%). the best among others in terms of results where it achieved an accuracy of 77 – 77.5% for experiment one without noise when the percentage of dominant eigenvalues are 80-82%.

4 Results

The algorithms under evaluation will high accuracy, execution time when the dominant eigenvalues are greater than 80%. Therefore, the results of the two experiments are shown in table 1.and table 2 for eignvalues of 80%, 82%, respectively.

The best results were achieved of eigenvalue of 92 %. These results are shown in table. 3.

Table 1. For dominant eigenvalues of 80%.

Method	Experiment I		Experiment II	
	Accuracy percentage (100%)	Execution Time (sec)	Accuracy percentage (100%)	Execution Time (sec)
PCA	64.750000	2.269562e-04	77.750000	1.835060e-04
2DPCA	74.500000	4.204432e-04	92.750000	2.521175e-04
DCT	77.500000	2.289460e-04	91.750000	1.692953e-04
SVM	68.000000	4.468349e-04	74.750000	3.102527e-04
LDA	51.500000	1.054715e-04	69.250000	1.439371e-04
ICA	44.000000	8.843073e-05	27.750000	7.164293e-05
Adding Gaussian - Salt & pepper noise				
PCA	64.500000 57.250000	2.241388e-04 2.246914e-04	78.750000 71.750000	1.990440e-04 1.799932e-04
2DPCA	74.00000 68.750000	4.207407e-04 4.155975e-04	92.500000 87.500000	2.320024e-04 2.343491e-04
DCT	77.000000 70.250000	2.305235e-04 2.287479e-04	92.000000 92.000000	1.636235e-04 1.621943e-04
SVM	67.500000 66.000000	2.975751e-04 3.156093e-04	74.000000 71.750000	2.433273e-04 2.996047e-04
LDA	50.250000 31.000000	8.675590e-05 8.891913e-05	66.250000 37.000000	7.060630e-05 7.038360e-05
ICA	39.250000 40.000000	8.953501e-05 8.938693e-05	27.750000 27.250000	7.319322e-05 7.297999e-05

Table 2. For dominant eigenvalues of 82%.

Method	Experiment I		Experiment II	
	Accuracy percentage (100%)	Execution Time (sec)	Accuracy percentage (100%)	Execution Time (sec)
PCA	65.000000	2.313472e-04	78.500000	1.967238e-04
2DPCA	74.500000	4.153176e-04	92.500000	2.282651e-04
DCT	77.000000	2.640794e-04	91.750000	1.592742e-04
SVM	70.250000	1.531384e-03	78.000000	7.396186e-04
LDA	53.000000	1.454943e-04	66.750000	1.134310e-04
ICA	43.000000	9.610512e-05	42.000000	8.558955e-05
Adding Gaussian - Salt & pepper noise				
PCA	64.500000 57.500000	2.393328e-04 2.389077e-04	79.000000 71.750000	1.989863e-04 1.960694e-04
2DPCA	74.000000 68.750000	4.223888e-04 4.112049e-04	92.500000 87.500000	2.328566e-04 2.341334e-04
DCT	76.750000 71.750000	2.659465e-04 2.604592e-04	92.000000 92.000000	1.607627e-04 1.595445e-04
SVM	70.000000 69.500000	1.286879e-03 1.107548e-03	77.750000 75.250000	7.921406e-04 7.164184e-04

LDA	52.000000 32.500000	1.127143e-04 1.065010e-04	65.750000 38.750000	8.243458e-05 8.627767e-05
ICA	39.750000 37.750000	9.424835e-05 9.168141e-05	41.500000 43.250000	8.340300e-05 9.454753e-05

Table 3. For dominant eigenvalues of 92%.

Method	Experiment I		Experiment II	
	Accuracy percentage (100%)	Execution Time (sec)	Accuracy percentage (100%)	Execution Time (sec)
PCA	65.250000	3.143307e-04	79.750000	2.676885e-04
2DPCA	73.000000	9.415765e-04	95.000000	4.676676e-04
DCT	75.250000	4.178719e-04	95.250000	2.721877e-04
SVM	74.000000	4.564133e-04	89.750000	4.047641e-04
LDA	58.250000	9.638375e-05	84.250000	1.096340e-04
ICA	55.500000	7.689389e-05	51.750000	9.242916e-05
Adding Gaussian - Salt & pepper noise				
PCA	65.250000 57.250000	3.123610e-04 3.103564e-04	79.500000 73.750000	2.676347e-04 2.708002e-04
2DPCA	72.750000 68.250000	9.052585e-04 8.870883e-04	94.750000 89.750000	4.828296e-04 4.712406e-04
DCT	75.250000 70.000000	4.095078e-04 4.071892e-04	95.250000 95.250000	2.710240e-04 2.663764e-04
SVM	73.750000 71.000000	2.458880e-04 2.662152e-04	89.000000 86.500000	2.972499e-04 3.558123e-04
LDA	58.750000 42.250000	7.157619e-05 7.223412e-05	80.500000 55.000000	9.510848e-05 9.822354e-05
ICA	52.500000 51.500000	7.357675e-05 7.542027e-05	51.000000 50.500000	1.089621e-04 1.018195e-04

5 Conclusion and Future work

Six algorithms have been proposed to solve the accuracy problem of the facial recognition using PCA, 2DPCA, LDA, SVM, ICA and DCT. Two experiments were applied to test these algorithms by studying the effect of two kind of noises (Gaussian and salt and Pepper).

The DCT algorithm were the best among others in terms of results where it achieved an accuracy of 77 – 77.5% for experiment one without noise when the percentage of dominant eigenvalues (100%) =80- 82%. While the accuracy for applying the Gaussian and salt and pepper noises were 77 and 71.75% when dominant eigenvalues equal 80 and 82%, respectively. For experiment two, the DCT algorithm achieved best results as well with an accuracy of 95.25% for without noise when the percentage of dominant eigenvalues =92. For applying the Gaussian and salt and pepper noises, the accuracy was 95.25% when dominant eigenvalues equal 92% for both.

In our ongoing research, we are studying the six different facial recognition algorithms PCA, 2DPCA, LDA, SVM, ICA and DCT in terms of the execution time (running speed) and memory usage. Moreover, new algorithms might be implemented on our proposed experiments and procedure. We are planning also to use another database using all these algorithms.

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