

## Comparison Of PCA Based And 2DPCA Based Arabic Sign Language Recognition System

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### Abstract :

*In order to simplify the communication between the deaf and normal people, several sign language recognition systems have been developed. In this paper an Arabic Sign Language (ArSR) recognition system were implemented using one-dimensional principal component analysis (PCA), and two-dimensional principal component analysis (2DPCA) respectively. The PCA and 2DPCA are used for image representation and recognition. Compared to PCA, 2DPCA based on 2D image matrices rather than 1D vectors so that the image matrix does not need to transform into a vector prior to feature extraction. Instead, an image covariance matrix is constructed directly using the original image matrices and its eigenvectors are derived for image feature extraction. The experimental result shows that both PCA and 2DPCA approaches have a good recognition rate and almost equal, but 2DPCA approach is more computational efficient than PCA.*

*Keyword; PCA. 2DPCA, Arabic sign language*

مقارنة استخدام طريق تحليل العنصر الرئيسي وطريق تحليل العنصر الرئيسي ثنائية الأبعاد في نظام تمييز لغة الإشارة العربية للصم

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### الخلاصة :

من اجل تسهيل التواصل بين الأشخاص الصم والبكم والأشخاص الطبيعيين، فإن العديد من أنظمة التعرف على الإشارة قد طورت. في هذا البحث تم تصميم وتنفيذ نظام التعرف على لغة الإشارة باستخدام طريقة أحادية البعد تحليل العنصر الرئيسي (PCA) وطريقة ثنائي البعد تحليل العنصر الرئيسي (2DPCA) على التوالي. وقد تم استخدام هاتان الطريقتان لتمثيل والتعرف على صور الإشارة. إن النتائج العملي تظهر ان كلتا الطريقتان نسبة تمييز صحيحة جيدة جدا وتقريبا متساوية، لكن طريقة ثنائية البعد اكثر كفاءة حسابيا من طريقة أحادية البعد.

## Section I: Introduction

The growing popularity of vision-based systems has led to a revolution in gesture recognition technology. Vision-based gesture recognition systems are primed for applications such as virtual reality, multimedia gaming and hands-free interaction with computers. Another popular application is sign language recognition, which is the focus of this paper <sup>[1]</sup>.

The sign language in Arab world has been recently recognized and documented. Many efforts have been made to design a reliable sign language recognition systems used by deaf people as an alternative to spoken language and to reduce the communication gap between deaf and hearing people by focusing on the recognition of Arabic letters <sup>[2][3]</sup>.

Generally, there are two main directions in sign language recognition. The first one is glove-based systems use motion sensors to capture gesture data. While this data is more attractive to work with, the gloves are expensive and cumbersome devices, which detract from the naturalness of the human-computer interaction. In addition, the second one is vision-based systems; on the other hand, provide a more natural environment within which to capture the gesture data <sup>[1]</sup>.

There are several methods used in Arabic sign language recognition system can be broadly classified into, image feature based and geometry feature based methods. Image feature based methods or template-based methods, estimate the correlation between a sign and one or more templates, which is later used during recognition. They capture and analyze the global features of a sign. Successful and efficient templates can be constructed using tools like Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), Principal Component Analysis (PCA), Kernel Methods, and Fisher's Linear Discriminate (FLD). In contrast, geometry feature-based methods concentrate on local shape features and their geometrical relationships <sup>[4]</sup>.

PCA is one of the most successful techniques that have been used in image recognition, compression and feature extraction. PCA is a statistical method used to reduce the large dimensionality of the data space (observed variables) to the smaller intrinsic dimensionality of feature space (independent variables), which are needed to describe the data economically. This is the case when there is a strong correlation between observed variables <sup>[5][6]</sup>.

In PCA, the covariance matrix has large dimension therefore the computation of eigenvectors is time consuming and the results are not always satisfactory. A new technique called two-dimensional PCA was developed in order to avoid these problems. As opposed to conventional PCA, 2DPCA is based on 2D matrices rather than 1D vectors. That is, the image matrix does not need to be previously transformed into a vector. Instead, an image covariance matrix can be constructed directly using the original image matrices. In contrast to the covariance matrix of PCA, the size of the image covariance matrix using 2DPCA is much smaller <sup>[5][7]</sup>.

This paper is organized as follows; Section II presents an Arabic sign language database. Section III describes the theoretical background of image pre-processing, PCA, and 2DPCA. Section IV presents the proposed system, and finally the result and discussion are described in sections V and VI respectively.

## Literature Review

Many researchers deals with sign recognitions systems for deaf people. In addition, the use of sign is not tied to age, gender or ethnicity.

In <sup>[3]</sup> an Arabic sign language recognition system was developed. This system used different architecture of recurrent neural networks and examines the ability of neural networks to assist in Arabic sign language recognition systems.

In <sup>[4]</sup> comparison was made between the PCA and 2DPCA as an image classifier. In this paper the performance of PCA and 2DPCA were compared for face recognition system.

An Arabic sign Language Alphabets translator system was developed in <sup>[8]</sup>. The proposed system deals with images of bare hands, which allow the user to interact with the system in a natural way.

In addition, a comparative study of hand gesture recognition system was introduced in <sup>[9]</sup>. The proposed system examines the efficiency of four different classification methods are, Subtraction method, Gradient method, PCA and Rotation Invariant.

## Section II: Arabic Sign Language Database

The database in this paper is built in collaboration with Al'Amal institution for deaf in Wasit province. The pictures are capture for three people who volunteered to perform the signs to generate samples for our study according to their textbook <sup>[10]</sup>. The database consist of nine sign of Arabic alphabet, each sign with 70 pictures as show in Figure (1). No restriction is imposing on background, sex, and age of the volunteers. Moreover, the volunteers have different color skins. The deaf signs are captures using digital camera SONY  $\alpha$ 55.

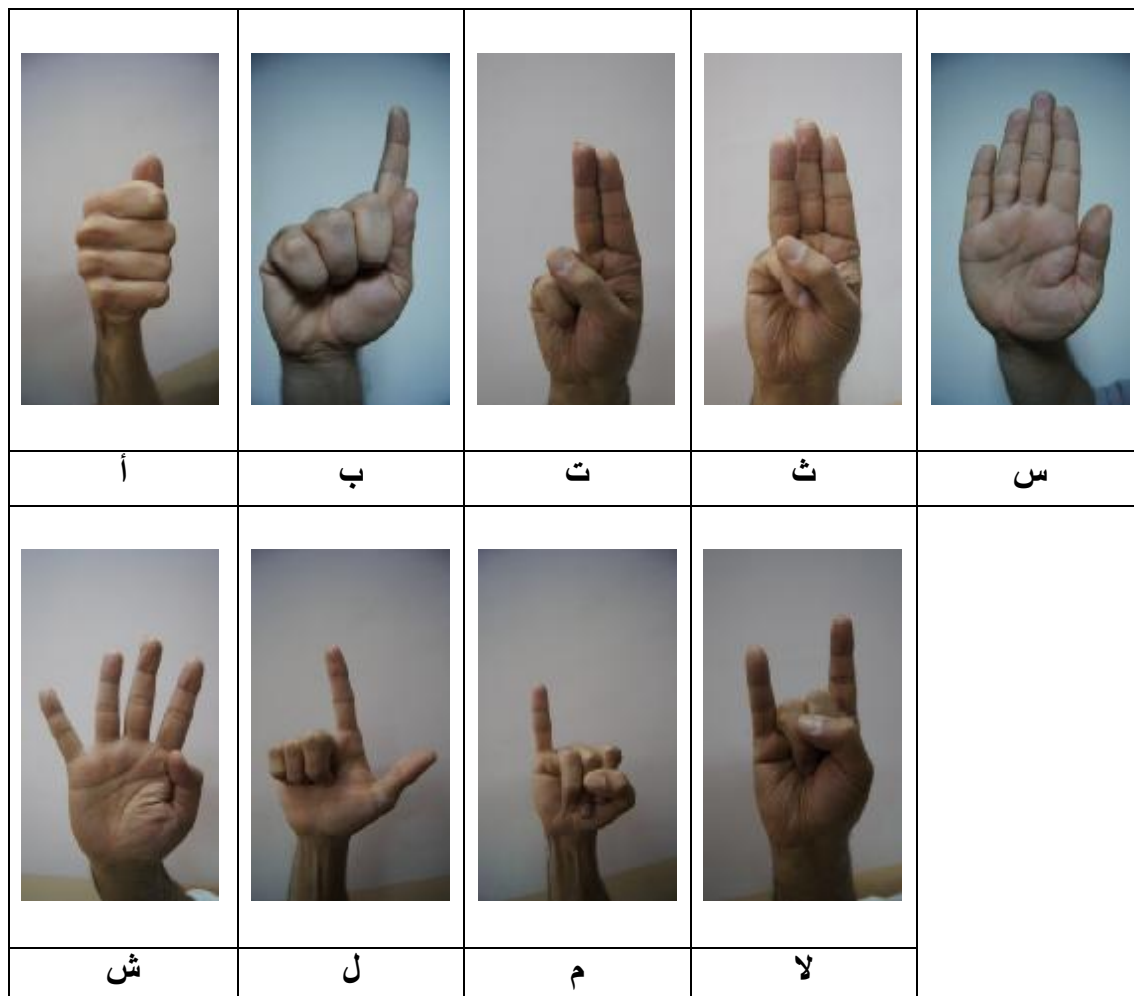


Fig. (1); Arabic Alphabet signs letters

### Section III: Theoretical background

#### 1- Skin color modeling and detection

Skin detection can be defined as the process of selecting which pixels of a given image correspond to human skin; it plays an important role in a wide range of image processing applications ranging from face detection, face tracking, gesture analysis, and content-based image retrieval systems and to various human computer interaction domains. There are some difficulties when detecting skin pixels. Skin color is affected by ambient light, which is unknown in many situations; different cameras produce different colors, even from the same person, under the same illumination conditions; and finally, skin colors change from person to person <sup>[11][12]</sup>.

#### 1-1 Color space used for Skin Modeling

The choice of color space can be considered as the primary step in skin-color classification. The RGB color space is the default color space for most available image formats. Any other color space can be obtained from a linear or non-linear

transformation from RGB. The color space transformation is assumed to decrease the overlap between skin and non-skin pixels thereby aiding skin-pixel classification and to provide robust parameters against varying illumination conditions. It has been observed that skin colors differ more in intensity than in chrominance. Hence, it has been a common practice to drop the luminance component for skin classification [11]. Several color spaces have been proposed and used for skin detection as listed below [11] [13] [14] [15].

#### A- Basic Color Space

- **RGB color model:** RGB is the most commonly used color space to represent digital images, since most of the image display devices have some sort of RGB output. It is being used in every computer systems as well as videos, cameras etc. Moreover, RGB benefits from its simplicity and easiness of implementation. RGB correspond to the three primary colors: red, green and blue, respectively
- **Normalized RGB color model:** Normalized RGB is obtained by normalizing RGB value to their first normalization using the following equation

$$r = \frac{R}{R + G + B} \quad 1$$

$$g = \frac{G}{R + G + B} \quad 2$$

$$b = \frac{B}{R + G + B} \quad 3$$

The sum of normalized RGB color is unity ( $r + g + b = 1$ ). Since the sum of these components is 1, the third component does not hold any significant information and is normally dropped to obtain a reduction in dimensionality.

- **CIE XYZ color model:** The CIE system describes color as a luminance component and two additional components X and Z. CIE-XYZ values were constructed from psychophysical experiments and correspond to the color matching characteristics of human visual system. The equations below shown the conversion process of normalized RGB to CIE XYZ color space:

If  $R', G', B' \leq 0.03928$  then

$$R = R' / 12.92 \quad 4$$

$$G = G' / 12.92 \quad 5$$

$$B = B' / 12.92 \quad 6$$

Otherwise

$$R = [(R' + 0.055) / 1.055]^{2.4} \quad 7$$

$$G = [(G' + 0.055) / 1.055]^{2.4} \quad 8$$

$$B = [(B' + 0.055) / 1.055]^{2.4} \quad 9$$

Then XYZ are equal to

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.41239079926596 & 0.35758433938388 & 0.18048078840183 \\ 0.21263900587151 & 0.71516867876776 & 0.07219281536073 \\ 0.01933081871559 & 0.11919477979463 & 0.95058215224966 \end{bmatrix} \times \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad 10$$

### B- Perceptual Color Spaces

- HSV color model:** Alay Ray Smith first introduced HSV- Hue, Saturation and value in 1978. V is the level of brightness. This color model is a simple and linear transformation from RGB. Hue defines the dominant color [such as red, purple and yellow] of an area. Saturation measures the colorfulness of the area in proportion of the brightness of the image. The conversion of RGB to HSV is given by the following equations:

$$H = \arccos \frac{\frac{1}{2}((R - G) + (R - B))}{\sqrt{((R - G)^2 + (R - B)(G - B))}} \quad 11$$

$$S = 1 - 3 \frac{\min(R, G, B)}{R + G + B} \quad 12$$

$$V = \frac{1}{3}(R + G + B) \quad 13$$

- TSV and TSL color model:** Saturation and value (Lightness) were used in skin detection. These spaces are more complex alternative to HSV. TSL is really best choice of color space for ‘Gaussian Skin color Modeling’. The conversions of normalized RGB to TSV and TSL are given by the following equations:

$$T = \begin{cases} \arctan(\frac{r}{g}) / 2\pi + \frac{1}{4} & \hat{g} > 0 \\ \arctan(\frac{r}{g}) / 2\pi + \frac{3}{4} & \hat{g} < 0 \\ 0 & \hat{g} = 0 \end{cases} \quad 14$$

$$S = \sqrt{\frac{2}{5}(r^2 + g^2)} \quad 15$$

$$L = 0.299R + 0.587G + 0.114B \quad 16$$

$$V = \frac{R + G + B}{3} \quad 17$$

Where

$$\hat{r} = r - \frac{1}{3} \quad 18$$

$$\hat{g} = g - \frac{1}{3} \quad 19$$

Moreover, r, g are calculated according to Equations 1, and 2 respectively.

### C- Orthogonal Color Spaces

- **YC<sub>b</sub>C<sub>r</sub> color model:** This color space i.e. YC<sub>b</sub>C<sub>r</sub> is commonly used by European TV system. Luminance (Y) and chrominance (Cb and Cr) are used to represent this color space as the equations below:

$$Y = 0.299R + 0.587G + 0.114B \quad 20$$

$$C_b = B - Y \quad 21$$

$$C_r = R - Y \quad 22$$

In this color space, chrominance and luminance are explicitly separated. This property and its simplicity made this color space is one of the most popular color space used in skin detection.

### D- Perceptually uniform color spaces

- **CIE Lab color space:** Perceptual uniformity represents how two colors differ in appearance to a human observer and hence uniform color spaces (UCS) were defined such that all the colors are arranged by the perceptual difference of the colors. However, the perceptual uniformity in these color spaces is obtained at the expense of heavy computational transformations. In these color spaces, the computation of the luminance (L) and the Chroma (a, b) is obtained through a non-linear mapping of the XYZ coordinates as show in equations below:

$$L = 116 * f\left(\frac{Y}{Y_n}\right) - 16 \quad 23$$

$$a = 500 * \left[ f\left(\frac{X}{X_n}\right) - f\left(\frac{Y}{Y_n}\right) \right] \quad 24$$

$$b = 200 * \left[ f\left(\frac{Y}{Y_n}\right) - f\left(\frac{Z}{Z_n}\right) \right] \quad 25$$

Where the function  $f$  is define as:

$$f(x)=x^{1/3}, \text{ if } x>0.008856 \quad 26$$

$$f(x)= 7.787x+0.137931 \text{ otherwise} \quad 27$$

Moreover, where  $X_n$ ,  $Y_n$ ,  $Z_n$  are calculated for a reference white point that depends on the illumination of the scene. This is usually described by the color temperature of the lamp.

## 1-2 Skin Segmentation

The final goal of skin color detection is to build a decision rule that will discriminate between skin and non-skin pixels [16]. The skin segmentation method can segment the wanted skin objects from background by choosing a suitable threshold, which is based on the different characteristics in gray-scale between the target and background. The most representative methods are histogram threshold, Otsu, the best entropy method, moment invariant method, and fuzzy clustering method. With the advantages of small amount of calculation, simple theory and easy implementation, Otsu is generally used in real-time image processing system [17].

- *Otsu method*

Otsu method was derived on the principles of discrimination and the theory of least square [17] [18]. There is an image with the gray-scale between one to  $m$ , the number of pixels with the value of  $i$  is  $n_i$ , then the total number of image pixels is:

$$N = \sum_{i=1}^m n_i \quad 28$$

The probability of appearing gray-scale pixel with the value of  $i$  is:

$$P_i = \frac{n_i}{N} \quad 29$$

Then, use  $T$  to split the gray scale into two groups,  $C_0=\{1\sim T\}$  and  $C_1=\{T+1\sim m\}$ . The formulas of the average and probability generated by each group are as follows:

$$\omega_0 = \sum_{i=1}^T p_i = \omega(T) \quad 30$$



$$\omega_1 = \sum_{i=T+1}^m p_i = 1 - \omega(T) \quad 31$$

And

$$\mu_0 = \sum_{i=1}^T \frac{ip_i}{\omega} = \frac{\mu(T)}{\omega(T)} \quad 32$$

$$\mu_1 = \sum_{i=T+1}^m \frac{ip_i}{\omega} = \frac{\mu - \mu(T)}{1 - \omega(T)} \quad 33$$

Where  $\mu$  is the formula of calculating the mean of the whole image as follows:

$$\mu = \sum_{i=1}^m ip_i \quad 34$$

And  $\mu(T)$  is the formula of calculating the average of the image when the threshold value is  $T$  as follows:

$$\mu(T) = \sum_{i=1}^T ip_i \quad 35$$

Therefore, the formula of the gray sample average is

$$\mu = \omega_0\mu_0 + \omega_1\mu_1 \quad 36$$

The formula for calculating the variance between the two groups is as follows:

$$\begin{aligned} \delta^2(T) &= \omega_0(\mu_0 - \mu)^2 + \omega_1(\mu_1 - \mu)^2 \\ &= \omega_0\omega_1(\mu_1 - \mu_0)^2 \\ &= \frac{[\mu\omega(T) - \mu(T)]^2}{\omega(T)[1 - \omega(T)]} \end{aligned} \quad 37$$

Seek the maximum value of the formula, when  $T$  is changing from one to  $m$ . Then  $T$  is the threshold and  $\delta^2(T)$  is the selecting function of  $\delta^2(T)$ .

## 2- Principal Component Analysis (PCA)

Principal component analysis or *karhunen-loève transformation* is standard technique used in statistical pattern recognition and signal processing for data reduction and Feature extraction. As the pattern often contains redundant information, mapping it to a feature vector can get rid of this redundancy and yet preserve most of the intrinsic information content of the pattern. These extracted features have great role in distinguishing input patterns. The jobs that PCA can do are prediction, redundancy removal, feature extraction, data compression, image processing, and coding (decoding) [6][19].

The method is concerned with the analysis of multivariate observations. These observations can describe anything from stock prices to biometrical data of the turtle. The basic idea comes from the fact that, in many such measurements, the  $n$  observation variables  $x_1, \dots, x_n$  can be well fitted by an  $m$  parametric surface where  $m$  is much smaller than  $n$ . This means that there are, in fact,  $m$  hidden degrees of freedom corresponding to some underlying parameters  $y_1, \dots, y_m$ . We can say that  $n$  is the superficial dimensionality of  $\mathbf{x}$ , while  $m$  is its intrinsic dimensionality. The hidden parameters  $y_i$  are called factors or features, and  $\mathbf{y} = [y_1, \dots, y_m]^T$  is the feature vector [20][21]. Therefore;  $\mathbf{x}$  can be compressed as:

$$\mathbf{y} = \mathbf{W}\mathbf{x} \quad 38$$

Where  $\mathbf{x}$  is consider to be a zero mean such as

$$\mathbf{x} = \mathbf{x} - m_x = \mathbf{x} - \frac{\mathbf{1}}{N} \sum_{i=1}^n x_i \quad 39$$

Matrix  $\mathbf{W}$  is determined by the covariance matrix  $\mathbf{C}_x$ . Rows in the  $\mathbf{W}$  matrix are formed from the eigenvectors  $\mathbf{e}$  of  $\mathbf{C}_x$  ordered according to corresponding eigenvalues in descending order. The evaluation of the  $\mathbf{C}_x$  matrix as

$$\mathbf{C}_x = \mathbf{x}\mathbf{x}^T \quad 40$$

The covariance matrix  $\mathbf{C}_x$  is a square, symmetric matrix of  $n \times n$  elements and by using Eigenvalue decomposition (EVD),  $\mathbf{C}_x$  will be:

$$\mathbf{C}_x = \mathbf{W}^T \mathbf{\Lambda} \mathbf{W} = \sum_{i=1}^n \lambda_i \mathbf{w}_i \mathbf{w}_i^T \quad 41$$

Where:  $\mathbf{W}$  is the Eigen vector matrix

$\mathbf{\Lambda}$  is a diagonal matrix of Eigenvalues

$\lambda$  Eigenvalue.

### 3- Two-Dimensional Principal component analysis (2DPCA)

Because of the PCA algorithm has a disadvantage of high computational complexity, a new technique called two-dimensional PCA was proposed to cut the computational cost of the standard PCA [22]. 2DPCA is developed for image feature extraction. As opposed to conventional PCA, 2DPCA is based on 2D matrices rather than 1D vectors. That is, the image matrix does not need to be previously transformed into a vector. Instead, an image covariance matrix can be constructed directly using the original image matrices. In contrast to the covariance matrix of PCA, the size of the image covariance matrix using 2DPCA is much smaller [23].

Compared with PCA, 2DPCA has three significant advantages: It is easier to evaluate the image covariance matrices. It consumes less time to compute feature vectors. In addition, it preserves the underlying geometric data structure for data analysis while PCA ignores the underlying local information [24].

Consider an  $M$  by  $N$  images as  $M \times N$  denoted by  $A$ . let  $x$  be an  $N$ -dimensional unit column vector. Projecting  $A$  onto  $x$  yields an  $M$ -dimensional vector  $y$  as [22]

$$y = Ax \quad 42$$

The purpose of 2DPCA is to select a good projection vector  $x$ . To evaluate the goodness of projection vector, the use of the total scatter of the projected samples is suggested, which can be characterized by the trace of the covariance matrix of the projected feature vectors. Thus, the criterion is to maximize the following:

$$J(x) = \text{tr}(S_x) \quad 43$$

Where  $S_x$  is the covariance matrix of the projected feature vectors, written by:

$$S_x = E(y - Ey)(y - Ey)^T = E[(A - EA)x][(A - EA)x]^T \quad 44$$

Hence,

$$J(x) = \text{tr}(S_x) = x^T E[(A - EA)^T(A - EA)]x \quad 45$$

Given a set of training images  $A(1), A(2), A(3), \dots, A(n)$ , Eq.(45) will be:

$$J(x) = x^T \left[ \frac{1}{N} \sum_{i=1}^n (A(i) - \bar{A})^T (A(i) - \bar{A}) \right] x \quad 46$$

Where

$$\bar{A} = \frac{1}{N} \sum_{i=1}^n A(i) \quad 47$$

Moreover, the covariance matrix  $G$  is equal to

$$G = \frac{1}{N} \sum_{i=1}^N (A(i) - \bar{A})^T (A(i) - \bar{A}) \quad 48$$

The optimal axis be the unit vector that maximizing  $J(x)$ , in other word the eigenvector of  $G$  corresponding to the largest eigenvalue.

## Section IV: The proposed system

The proposed system of Arabic sign language recognition consists of two main phases, which is; Image Pre-processing, and PCA or 2DPCA classifier. Figure (2) shows the structure of the system.



Fig. (2): The proposed system of Arabic sign language recognition

### 1- Image Pre-Processing

The Pre-processing stage receives, as an input image that contains the signed letter to be translated into text, and prepare it to be ready for use in classifier phases as shown in Figure (3).



Fig. (3): The image Pre-Processing stage

The following steps demonstrate the Pre-processing session:

- The RGB images are received from the digital camera as shown in Figure (4-a).
- Convert the RGB image to CIE Lab color image using Equations (23-24-25-26-27) as shown in Figure (4-b).
- Selecting the Chroma (b) image from the CIE Lab image as shown in Figure (4-c).
- Find the threshold value for the selected image using Otsu method, which chooses the threshold to minimize the interclass variance of the Threshold black and white pixels using Equations (28,29,30,31,32,33,34,35,36,37).
- Convert the selected image to binary image using threshold value as shown in Figure (4-d).
- Convert the RGB image to gray image as shown in Figure (4-e).
- Multiply the gray image by the binary image. With this step, the hand is determined as an object and isolated from the background as show in Figure (4-f)
- Eliminating the wrist portion that is unnecessary for further analysis. The elimination of the wrist is done by calculating the number of 1's in each row of the image and determine the cutting row that have low numbers of 1's pixel for the lower portion of the image as show in Figures (4-g) and (4-h).
- Cropping the binary image from the top, right, and left sides to fit the hand inside the image as show in Figure (4-i).
- Convert the cropped image to square dimension and resize it to 200×200 pixels as show in Figure (4-j).

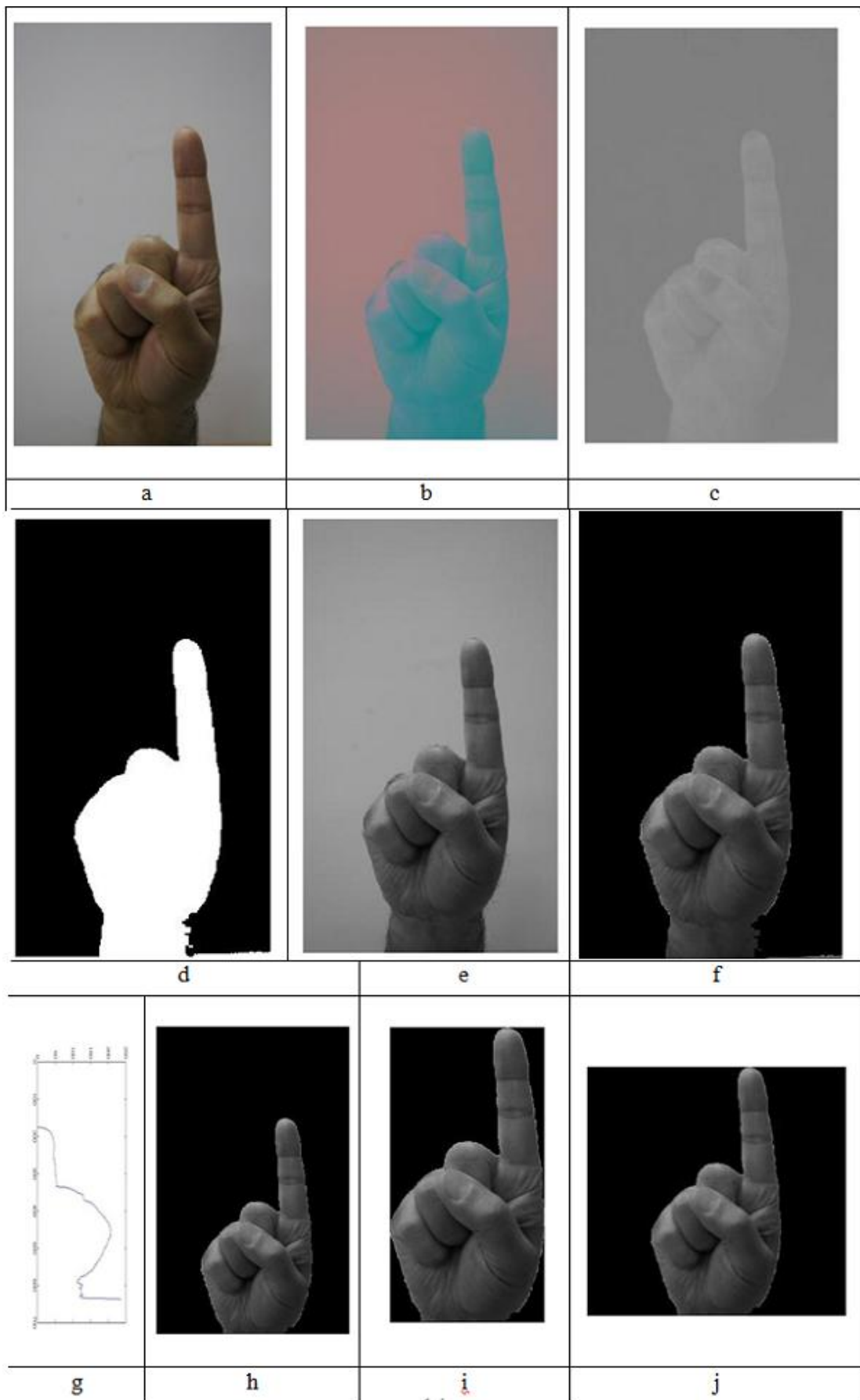


Fig. (4): The illustration of Image Pre-processing

## 2- The classifier

In this stage the sign images are classified using the eigenvectors method, whether it belong to a specific alphabet letters. The classification process is shown in Figure (5). In this paper a comparison was made between PCA classifier and 2DPCA classifier. The Classification process involved two phases, Training phase and recognition phase.

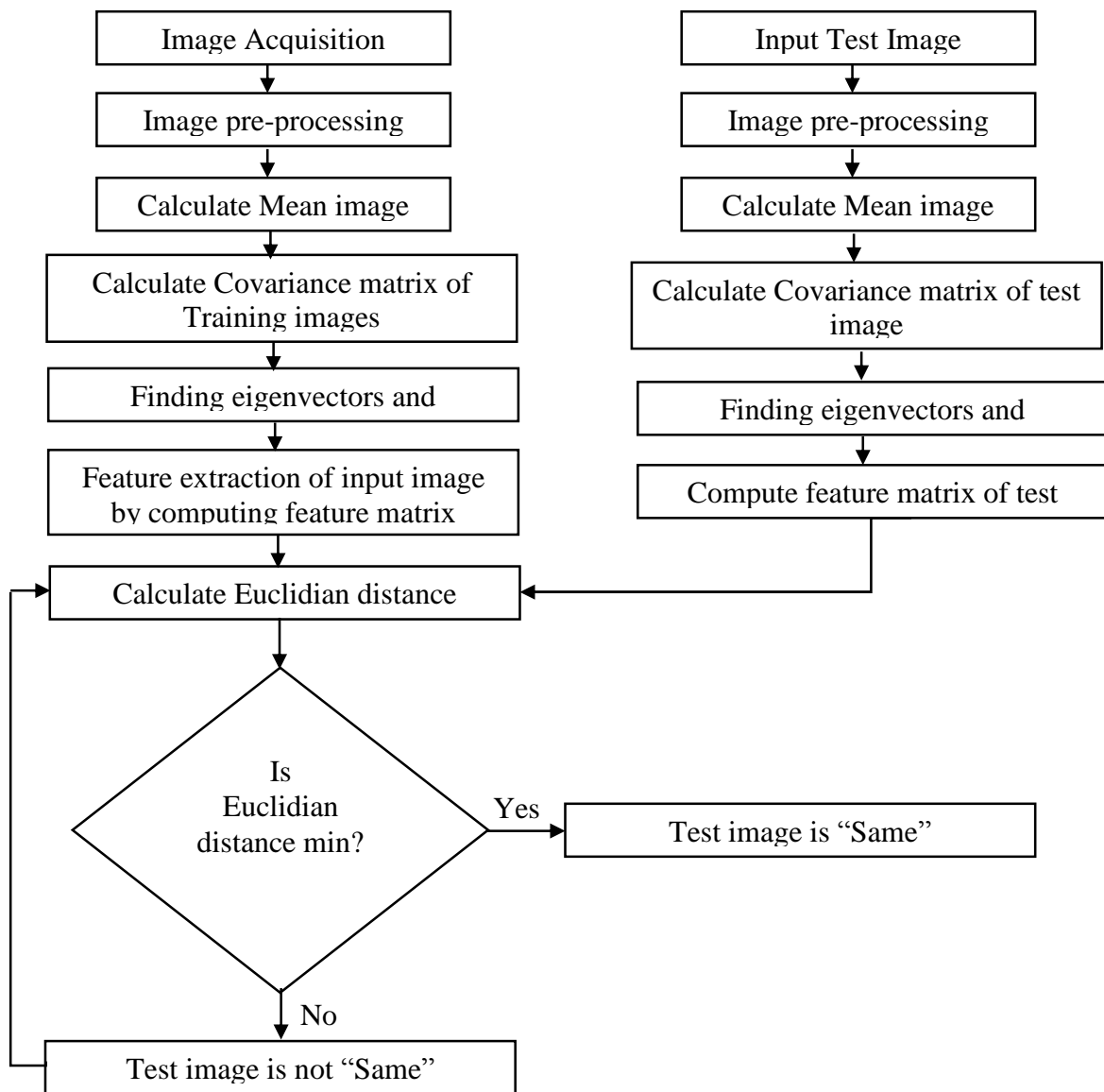


Fig. (5); The flowchart of the Classification process

## A- PCA classifier

The training phase of PCA classifier is illustrated as:

- Applying pre-processing techniques to all training images and rearrange each image from 2-dimensional to 1-dimensional matrix.
- Build the data matrix  $A$  of 1-dimensional training image with a label vector  $L$  having the corresponding alphabet names of the image columns in  $A$ .
- Get mean column vector  $m$  of the data matrix  $A$  as

$$m_i = \frac{1}{N} \sum_{j=1}^N \alpha_{i,j} \quad 49$$

Where  $i = 1, 2, 3, \dots, 40000$  (No. of pixels= $M \times N = 200 \times 200 = 40000$ )

$N =$  No. of training images.

- Subtract mean  $m$  from each of the columns of  $A$  to result in mean centered matrix  $A$  as

•

$$\bar{\alpha}_i = \alpha_i - m \quad 50$$

Where  $i = 1, 2, 3, \dots, N$  (No. of training images)

- Compute the covariance matrix  $C_A$  of  $A$  as  $C_A = AA^T$
- Obtain eigenvectors matrix  $E$  and eigenvalues vector  $V$  of  $C$ .
- Rearrange the eigenvector columns in  $E$  as the corresponding eigenvalues in  $V$  are sorted in descending order.
- Project the centered matrix  $A$  onto  $E$  to get feature matrix  $F = E^T A$ .

The Recognition Phase is:

- Apply the pre-processing technique on test image  $B$ , and rearrange it from 2-dimensional to 1-dimensional matrix  $z$ .
- Subtract the mean vector  $m$  from the image vector  $z$  as:

$$\bar{z} = z - m \quad 51$$

- Project the image vector  $\bar{z}$  onto the Eigen matrix  $E$  to get the feature vector  $b = E^T \bar{z}$ .
- Compute the Euclidian distance  $d$  between the feature vector  $b$  and all the column vectors in the feature matrix  $F$  and identify the column having the minimum distance  $d$ .
- Obtain the label from vector  $L$  corresponding to the column identified in  $F$  having the minimum distance to  $\bar{z}$ .



## B- 2DPCA classifier

The training phase of 2DPCA classifier is listed as:

- Applying pre-processing techniques to all training images.
- Build the three dimensional (x,y,z) data matrix  $A$ , where (x,y) represented the image dimensions and z represented the number of training images, and constructed a label vector  $L$  having the corresponding alphabet names of the image matrix in  $A$ .
- Obtain the average image  $\bar{A}$  of all training images as:

$$\bar{A} = \frac{1}{Z} \sum_{i=1}^Z A_i \quad 51$$

Where Z=No. of training images

$A$ = image matrix

- Estimate the image covariance matrix  $G$  as

$$G = \frac{1}{Z} \sum_{i=1}^Z [(A_i - \bar{A})^T (A_i - \bar{A})] \quad 52$$

- Compute the orthogonal eigenvectors  $x_1, x_2, \dots, x_d$  corresponding to the d largest non-zero eigenvalues of  $G$ .
- Constructed the feature matrix  $X$ , where  $X=[x_1, x_2, x_3, \dots, x_d]$ .
- Compute the principal component matrix  $Y$  of each training image by

$$Y_z = A_z \times X \quad 53$$

Where  $z= 1,2,3, \dots$  (No. of Training images)

The Recognition Phase is:

- Apply the pre-processing technique on test image  $B$ .
- Subtract the average image from the test image as

$$\bar{B} = B - \bar{A} \quad 54$$

- Compute the principal component matrix of the test image as:

$$Y_B = \bar{B} \times X \quad 55$$

- Compute the Euclidian distance between the  $Y_B$  and  $Y_z$  as

$$dist_z = \|Y_B - Y_z\|^2$$

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Where  $z=1,2,3,\dots$  No. of training images

- Minimum value of  $(dist_z)$  is corresponding the correct alphabet sign image in vector  $L$ .

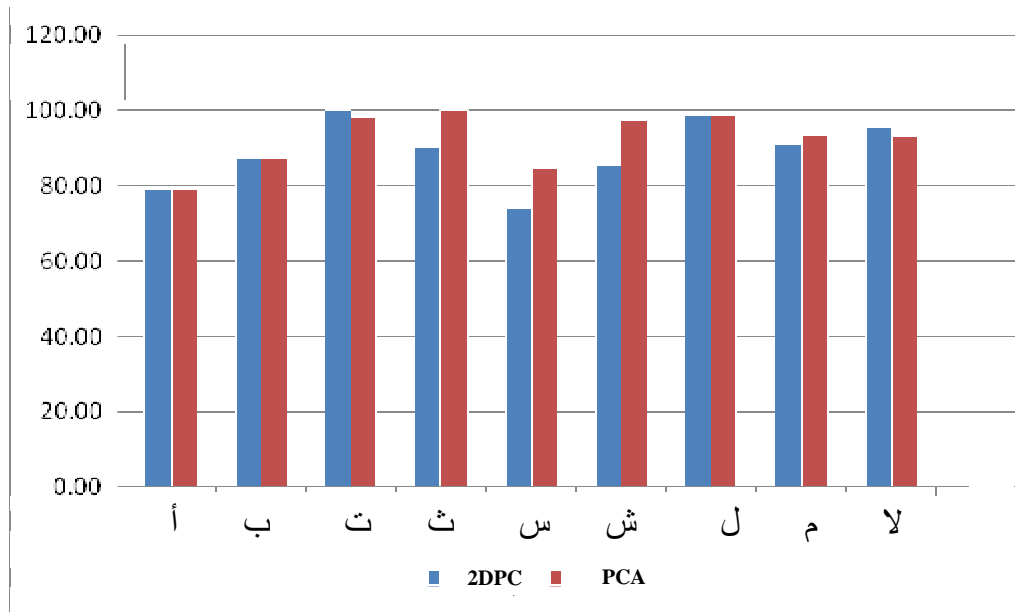
## Section VI: Result and discussion

The proposed system was implemented using a laptop of (2.27 Core I5, and 4GB RAM, Microsoft Windows 7 platform) with a MTLAB v.7.10 (R2010a) program. The images are capture with a resolution of  $360 \times 460$ . The image database are divided into two groups, the first one is the training database of 405 images (9 sign letters of 45 images each sign), and second one is the testing database of (9 sign letter of 30 images each one). All images in the database are pre-processed and prepare it to the classifier. The PCA classifier and 2DPCA classifier are trained using 405 training images and tested. The recognition rate of PCA and 2DPCA classifiers are shown in Figure (6).



**Fig. (6); The recognition rate of PCA and 2DPCA classifiers using 405 training samples**

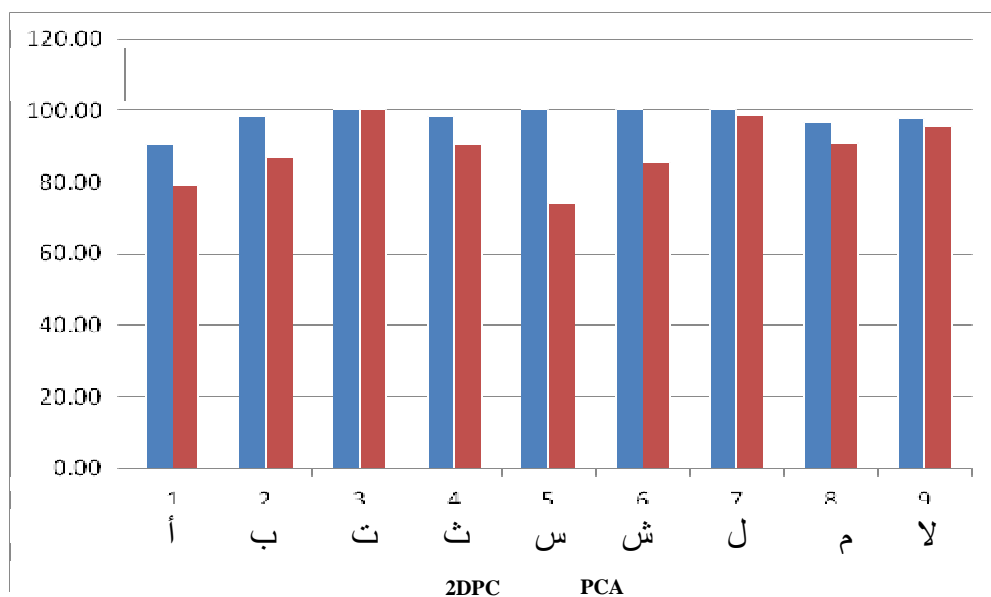
To discover the strength of the classifiers, The PCA and 2DPCA classifiers were trained using 90 images and tested. The recognition rate of PCA and 2DPCA classifiers are shown in **Figure (7)**.



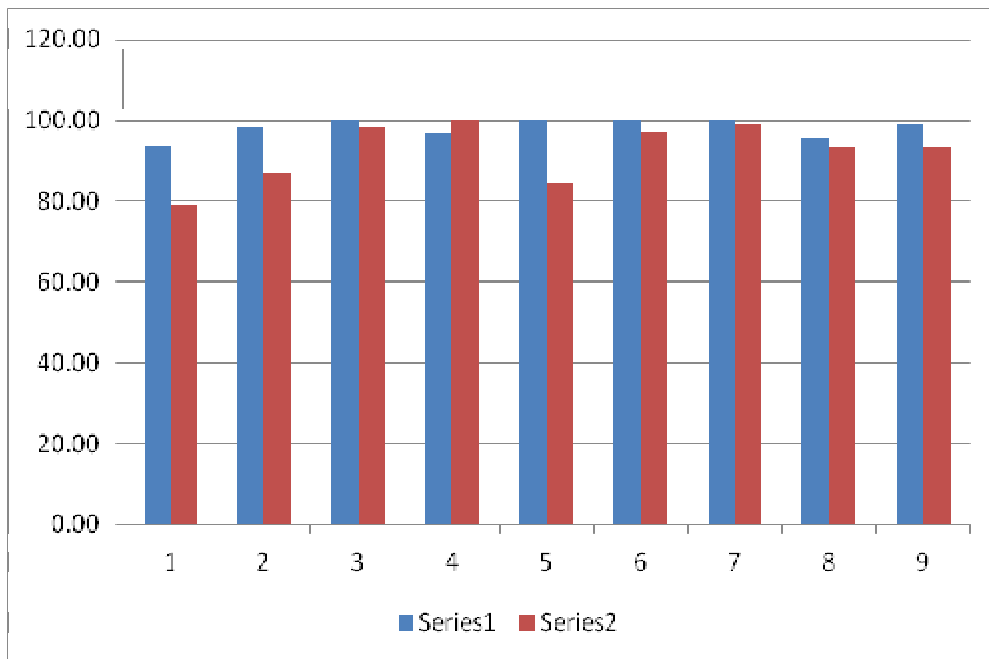
**Fig. (7); The recognition rate of PCA and 2DPCA classifiers using 90 training samples**

**Figure (6)** show a small difference between the recognition rate of PCA and 2DPCA when the training images are 405 images; in other words the training images larger than the pre-processed image dimension (200 pixels). In contrast, **Figure (7)** describes difference between the recognition rate of the two classifiers when the training images are 90 images; or less than the dimension of pre-processed image (200 pixels).

In order to show the effect of increasing the training image on the recognition rate, **Figures (8) and (9)** reveal that the recognition rate was increased gradually when the training images are increased.

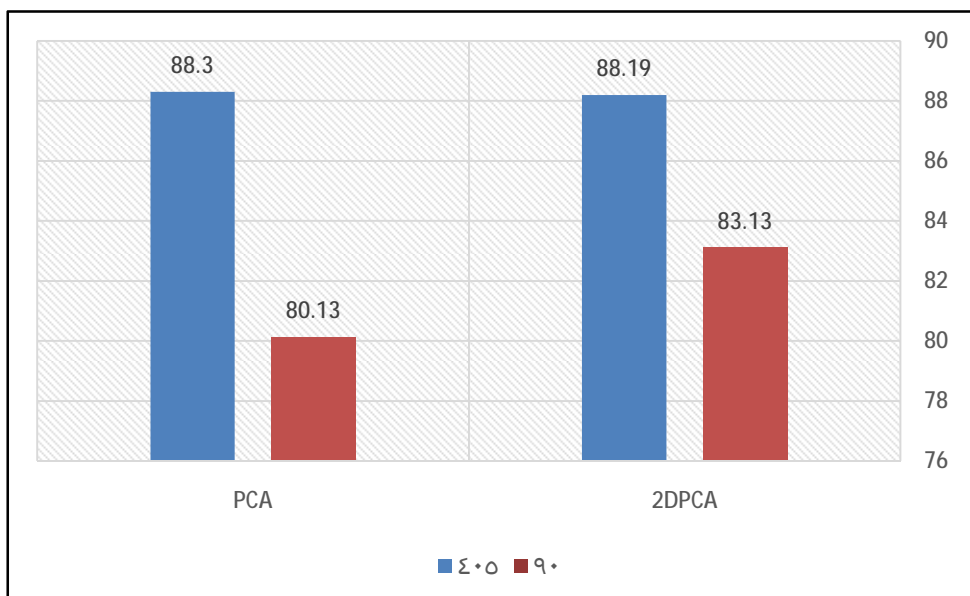


**Fig. (8); The comparison between 405 and 90 training image using PCA classifier**



**Fig. (9); The comparison between 405 and 90 training image using 2DPCA classifier**

The complete recognition rates are shown in **Figure (10)**



**Fig. (10): The Recognition rate of PCA and 2DPCA using 405, and 90 samples**

## Section VI: Conclusion

This paper describes the design and implementation of Arabic sign language recognition system. The propose system consist of two main stage which are; image pre-processing stage and classification stage. A comparison was made to discover the performance of the two classifiers. The experimental results show that in Figures (6) and (7) the recognition rate using PCA algorithm is larger than the 2DPCA algorithm (88.3 and 88.13 respectively for 405 training images) and (83.13 and 80.13 respectively for 90 training images). Moreover, by increasing the training images the recognition rates are increased by using PCA classifier (increased from 83.13 to 88.30) and by using 2DPCA classifiers (increased from 80.13 to 88.19). As a result the recognition rate of PCA is larger than 2DPCA for sign language recognition.

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