

Hand Image Verification Method Based on PCA Eigenvectors

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Abstract

In this research, the Principal Component Analysis (PCA) based method (namely Eigenhand), is used to verify persons from their hand's image. Our approach treats the hand recognition/verification problem as an essentially 2D-problem rather than requiring recovery of 3D geometry, taking advantage of the fact that hand's images can be described by a small set of 2D characteristics features. Here, the features are referred as "Eigenhands" because they represent the eigenvectors of the set of the trained and tested hands. The verification operation between the trained hand's images (i.e. preserved in the Database) and the input "unknown" hand image is performed by utilizing the Minimum-Mean-Distance "MMD" criterion. Several amounts of different noises (i.e. Gaussian, Uniform, Salt-and-pepper) have been added to the test hand to measure the reliability of our presented verification system in the presence of the noise. Invariant tests against image rotation, resizing, shifting have also been carried.

Keywords: <Hand verification, Hand recognition, Hand identification>

طريقة للتحقق من صور اليد تعتمد المتجهات الذاتية لتحويلة المركبات الأساسية

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العراق، بغداد، الجادرية

الخلاصة

تم في هذا البحث استخدام تحويلية المركبات الأساسية (صور اليد الذاتية) للتحقق من الأشخاص بواسطة صور أيديهم. تم الاستعاضة عن استخدام صور ثلاثية الأبعاد بصور ثنائية الأبعاد في عمليات التحقق و التمييز لغرض اختزال كمية الخصائص اللازمة في وصف الصور. تم الإشارة إلى تلك الخواص بالأيدي-الذاتية بسبب تمثيلها بواسطة المتجهات الذاتية لمجموعة الصور المجربة و الصور المختبرة. عملية التحقق بين الصور المجربة والمختبرة تم إجرائها باستخدام معيار المعدل-الأصغر-للمسافة. تم إضافة كميات مختلفة من الضوضاء المتنوعة (كاوسية، منتظمة، ملحبة-بهاراتية) إضافة لعمليات تدوير و إعادة تحجيم و إزاحة الصور المختبرة للتأكد من استقرارية نتائج الاختبارات المجربة بواسطة البرنامج المصمم في بحثنا هذا.

1.Introduction

Fingerprints recognition, face recognition, and iris recognitions have been active research areas over the past 40 years. They have been studied by scientists from different areas of psychophysical and computer sciences. The psychologists and neurosciences mainly deal with the human perception part of the topic, while engineers deal with machine recognition of studied features, [1]. In fact, the hands recognition application, as well as the faces, irises, and fingerprints have wide applications in the fields of security, biometric, access control, and surveillance systems. Biometric applications include; face recognition, fingerprint identification, iris identification, voice recognition, signature recognition, retina identification, and hand geometry identification [2].

Most of the attempts to identify the hands have been restricted environmentally; e.g. hand's skin color is surprisingly uniform and, therefore, utilizing color-based methods for detecting hand's type could be possible, for instance see [3-5]. In fact, little works have been done on hand's recognition in monochromatic images, they mostly based on their appearance and their textures. As an example, Wu and Huang [6], have investigated the suitability of a number of classification methods to prove the view independence of hand posture recognition; the objective was to perform hands classification without considering their skin color. However, the best pattern recognizers in most instances are humans, yet we do not understand how humans recognize patterns, [7].

One of the simplest and earliest approaches to pattern recognition are those based on template matching (used to determine the similarity between two entities of the same type). The similarity measure may be performed by determining the cross-correlation-coefficient between the matched templates, [8].

Other widely used approaches were those utilized statistical features. The goal of these recognition methods is to choose

features that allow pattern vectors belonging to different categories to occupy compact and disjoint regions in a d-dimensional feature space, [9, 10]. The effectiveness of these representations is determined by how well patterns from different classes can be separated. Statistical features may include probabilistic measures (e.g. mean, variance/standard deviation, and entropy values), they may be extracted from the 2D-histograms (i.e. the Co-Occurrence matrices), [11]. Moreover, the statistical methods may include measuring the correlation, the principal component analysis (PCA), the linear discrimination analysis (LDA), etc, [12, 13].

Transform based approaches have been proposed as alternative recognition methods utilizing frequency coefficient features; e.g. Discrete Cosine transform DCT, Fourier transform, Wavelet transform are examples of these transformation approaches [14-16]. Neural network approaches have also been used in pattern recognition generally in a geometrical local feature based manner, [17]. In this recognition system, the obtained fractal codes are fed as inputs to a back-propagation neural network for identifying an individual.

Practically, structural or texture based approaches have proved its superiority in yielding best classification and recognition results in varying image environments. This recognition approach is, in fact, intuitively appealing because, in addition to recognition ability, it provides a description of how the given pattern is constructed from the primitives, [18, 19]. The method presents in this paper can be consider as to be hybrid recognition technique which based on both synthetic and structural features.

2. Preprocessing Operations:

The design of a pattern recognition system essentially involves the following three aspects: data acquisition and preprocessing, data representation, and decision making. The preprocessing step

includes segmenting the object of interest from the background using grey tone thresholding/edge detection methods, image noise reduction using spatial/frequency domain filters, image contrast enhancement methods using histogram equalization/modification methods, etc.

2.1 Image segmentation by thresholding and/or edge detection processes:

Image segmentation is an essential preliminary step in most automatic pictorial pattern recognition and scene analysis problems. It is a fundamental tool in image processing and computer vision, particularly in the areas of feature detection and feature extraction, which aim to recognize and/or identify certain patterns.

Because of its intuitive properties and simplicity of implementation, image thresholding play a central position in applications of image segmentation. Thresholding may be viewed as an operation that involves tests against a function T of the form [20];

$$T = T[x, y, \mu(x, y), f(x, y)] \quad (1)$$

where $f(x, y)$ is the gray level of point (x, y) and $\mu(x, y)$ denotes some local property of this point—for example, the average gray level of a neighborhood centered on (x, y) . A thresholded image $g(x, y)$ is defined as;

$$g(x, y) = \begin{cases} 1 & \text{if } f(x, y) > T \\ 0 & \text{if } f(x, y) \leq T. \end{cases} \quad (2)$$

As an example, see Fig.(1), the original hand image, its histogram, and its thresholded versions (T=50, 100, and 128, respectively).

Image segmentation algorithms generally are based on one of two basic properties of intensity values: i.e. **discontinuity** and **similarity**. In the first category, the approach is to partition an image based on abrupt changes in intensity, such as **edges** in an image, while the approaches in the second category are based on partitioning an image into regions that are similar

according to a set of predefined criteria. Thresholding (discussed above), region growing, and region splitting and merging are examples of methods in this category, [20]. However, the approaches used to detect discontinuities in image gray values are, usually, referred as edge detectors. Several techniques for detecting edges have been developed and used to delineating regions within an image. The simplest types of these detectors are based on implementing differential/gradient “∇” operator and assigned all differentiated points having values above certain threshold to as edges. For an image function $f(x, y)$, the differentiated image $g(x, y)$ is given by;

$$g(x, y) = |\nabla f(x, y)| = \sqrt{\left(\frac{df(x, y)}{dx}\right)^2 + \left(\frac{df(x, y)}{dy}\right)^2} \quad (3)$$

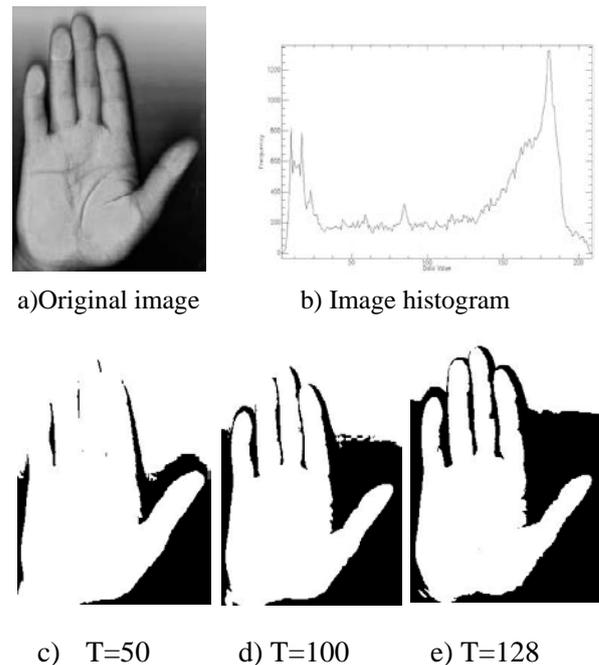


Figure (1): a) original hand image, b) its histogram, c-e) thresholded versions with different threshold values (T = 50, 100, and 128).

Examples of the most commonly used gradient masks are shown in Fig.(2). The problem with the differential/gradient edge detection techniques lies in their dependent on threshold value; i.e. utilizing large threshold producing disconnected

boundaries, while using small threshold value creates thick boundaries (i.e. undesired edge points are also detected), as illustrated in Fig.(3).

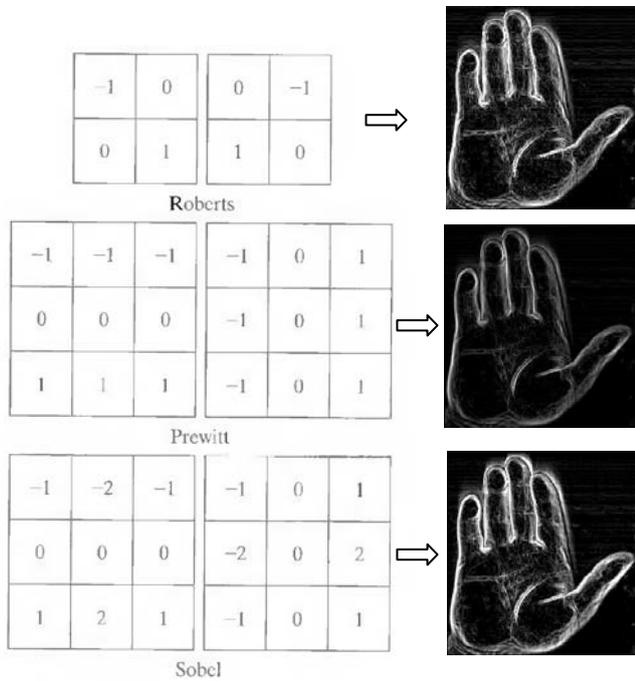


Figure (2): Digital representation of the most common used gradient operators (left), their performances on the hand image (right).

To overcome the threshold dependency problems associated with the gradient edge detectors, several edge techniques have been introduced based on convoluting the image with a band-pass filter (e.g. Laplacian of Gaussian Operator), detecting the zero-crossing points as edge points. Examples of these edge detectors are Marr-Hildreth [21], Geuen [22], and Canny techniques [23]. The edge detection processes by these techniques is illustrated in Fig. (4).

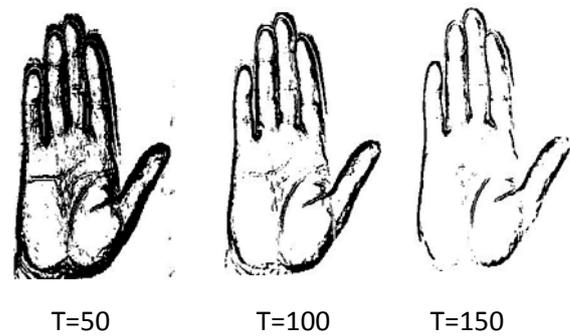


Figure (3): Thresholded versions of Sobel gradient image, using different threshold values.

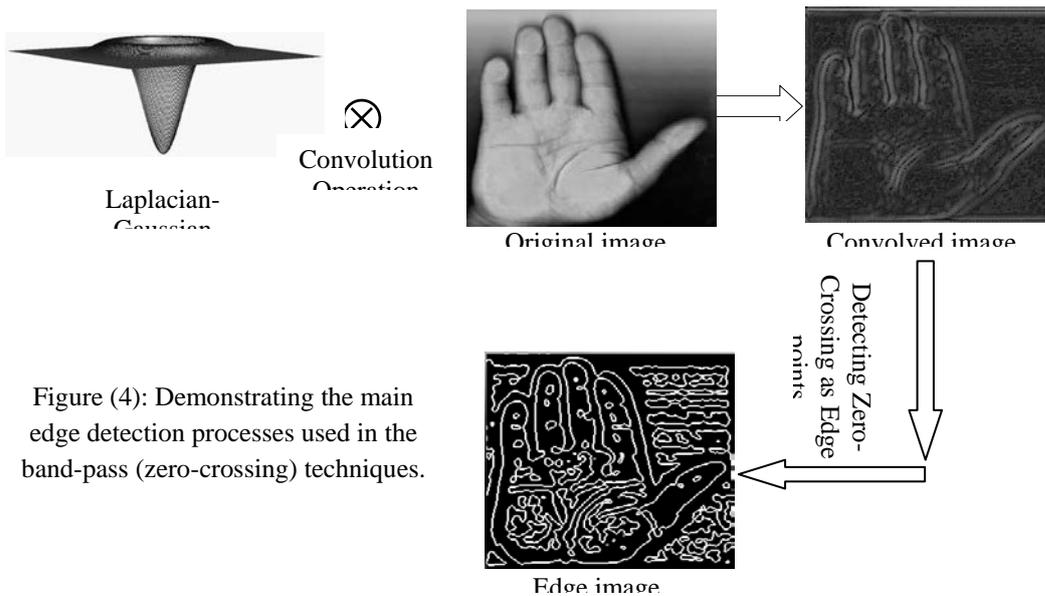


Figure (4): Demonstrating the main edge detection processes used in the band-pass (zero-crossing) techniques.

2.2 Image Enhancement Processes:

The idea behind enhancement techniques is to highlight certain features of interest in an image, or simply may be used to reduce the effects of certain undesired signal or noise within the image. The principal sources of degradation (e.g. noise, bad illumination, camera motion, etc) in digital images arise during image acquisition (digitization) and/or transmission. For instance, the major factors affecting the amount of noise during acquiring images with a CCD camera are the light levels and sensor temperature. The corruption in images during transmission is due to interference in the channel used for transmission. For example, an image transmitted using a wireless network might be corrupted as a result of lightning or other atmospheric disturbance [20].

For example, the hand image used in figures above has been badly illuminated during image acquisition, therefore the edge image in Fig.(4) showed undesired edge lines at the image’s background. To overcome this problem, image thresholding may be used to assign as edges only those points having zero-crossing values (in the band-pass image) larger than certain desired threshold value “ T_1 ”. Example of edge images, obtained by implementing Canny’s method with filter’s standard deviation $\sigma=2$ and different zero-crossing threshold values, are shown in Fig.(5).

During acquisition, the image may be blurred by planar motion caused by camera movement. If D is the duration of the camera exposure, and $x_0(t)$ and $y_0(t)$ be the time-varying components of the motion in the x and y directions. The output blurred image by uniform linear motion, thus, can be represented by [24];

$$g(x, y) = \int_0^D f[x - x_0(t), y - y_0(t)]dt \quad (4)$$

Where $f(x, y)$ is the unaffected image.

The motion components can be estimated by the zeros of the Fourier transform of the blurred image function; i.e.

$$G(u, v) = F(u, v)H(u, v) = F(u, v) \int_0^D \exp^{-j2\pi[ux_0(t)+vy_0(t)]} dt \quad (5)$$

Where; $x_0(t)=Xt/T$ and $y_0(t)=Yt/T$ represent the rates of motion in the x and y directions, X and Y represent the total distances of image displacement in the x and y directions.

The *spectrum* of the blurring function in eq.(5), can be proven to be;

$$|H(u, v)| = DXY \left| \frac{\sin(\pi u X)}{\pi u X} \right| \left| \frac{\sin(\pi v Y)}{\pi v Y} \right| \quad (6)$$

Figure (6) shows three-dimensional (3D), two-dimensional (2D), and one-dimensional (1D) views of the Fourier spectrum for the blurring function $|H(u, v)|$, illustrating the zeroes that are used to estimate the motion components.

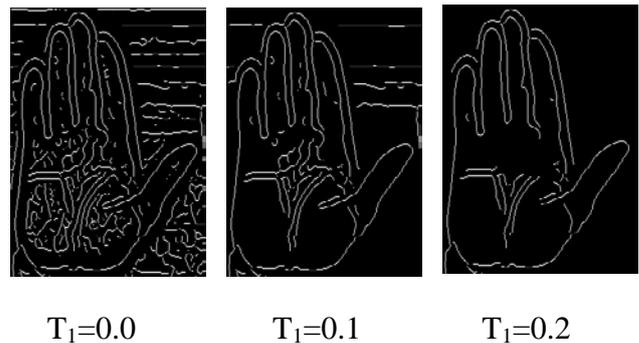


Figure (5): Edge images obtained by Canny’s method ($\sigma=2$) with different illustrated zero-crossing threshold values.

The X and Y components of the motion can now be estimated from the zeroes position on the horizontal and vertical frequency coordinates of the Fourier spectrum of $|H(u, v)|$; i.e.

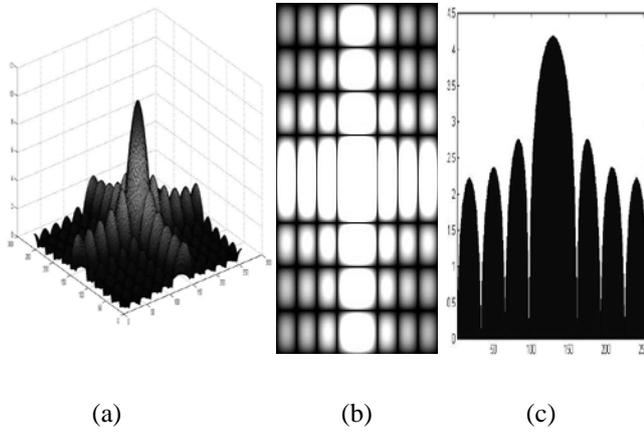
$$X = \text{round}\left(\frac{v_n}{4n}\right) \quad \text{and} \quad Y = \text{round}\left(\frac{u_n}{4n}\right),$$

where u_n & v_n represent, respectively, the n^{th} zero’s positions on the u & v axes.

As the motion components X & Y are estimated, the blurred image by the motion can be de-blurred, using any de-blurring filter (as an example, the parametric Wiener filter), for instance see [20]. Generally, degraded image is presented in the spatial domain by;

$$g(x, y) = h(x, y) * f(x, y) + \eta(x, y) \quad (7)$$

The symbol “*” indicates convolution.



a) 3D-plot of the $|H(u, v)|$
 b) 2D-image of $|H(u, v)|$
 c) 1D-plot of the $|H(u, v)|$

Figure(6):multidimensional views for the Fourier spectrum $|H(u, v)|$ of the motion cause blurring function.

In the frequency domain, eq.(7) is represented by;

$$G(u, v) = H(u, v) F(u, v) + N(u, v) \quad (8)$$

As mentioned above, $H(u, v)$ represents the blurring function caused by certain degradation phenomenon, while $\eta(x, y)$ or, alternatively $N(u, v)$ in the frequency domain, represents the principal sources of noise that may be arisen during image acquisition (digitization) and/or transmission operations. Too many types of different noises are existed; the following represent the most common of them:

- **The Gaussian Noise:** it is also called *normal* noise model, the Probability Density Function “PDF” of the Gaussian noise is-given by:

$$\rho(z) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(z-\mu)^2}{2\sigma^2}} \quad (9)$$

Where z represents the image gray level, μ is the mean of the average value of z , and σ is its standard deviation.

- **The Rayleigh Noise:** the PDF of this noise is given by

$$\rho(z) = \begin{cases} \frac{2}{b}(z-a)e^{-\frac{(z-a)^2}{b}} & \text{for } z \geq a \\ 0 & \text{for } z < a \end{cases} \quad (10)$$

The mean and variance of the Rayleigh noise is given by;

$$\mu = a + \sqrt{\frac{\pi b}{4}}, \text{ and } \sigma^2 = \frac{b(4-\pi)}{4}$$

- **The Uniform Noise:** it has the following PDF

$$\rho(z) = \begin{cases} \frac{1}{b-a} & \text{if } a \leq z \leq b \\ 0 & \text{otherwise} \end{cases} \quad (11)$$

It has the mean and variance values

$$\mu = \frac{a+b}{2}, \text{ and } \sigma^2 = \frac{(b-a)^2}{12}$$

- **The Impulse (Salt and Pepper) Noise:** The PDF of this (bipolar) impulse noise is given by

$$\rho(z) = \begin{cases} P_a & \text{for } z = a \\ P_b & \text{for } z = b \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

If $b > a$, gray-level b will appear as a light dot in the image (i.e. Salt noise mode), conversely, level a will appear as dark dot (i.e. Pepper noise mode) if either P_a or P_b is zero (in such case the noise is called *unipolar*). The PDFs of the above mentioned noises are illustrated in Fig.(7).

For the past three or four decades too many digital filtration methods (in both the spatial and frequency domains) have been developed to reduce the effects of the noise within the images. The most common used spatial domain’s filters are the mean and order-statistics filters, while the well known

frequency's filters are the low-pass and high-pass filters, for the details see Gonzalez and Woods [20].

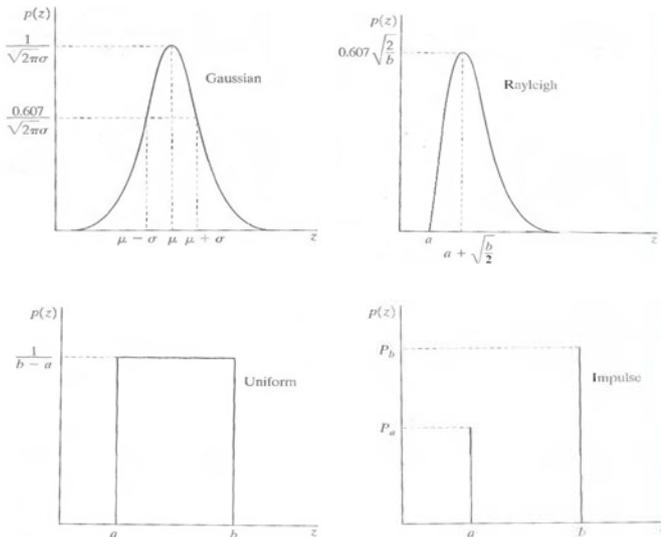


Figure (7): PDFs of several most common practical noise models.

3. Pattern Classification Basics:

Pattern recognition is the science that concerns the description or classification of measurements. A typical pattern recognition system takes the input data, extracts the features, trains the classifier and evaluates the test pattern. There are three main pattern recognition approaches; i.e. *statistical*, *syntactic*, and *neural* pattern recognition approaches [7]. In this research, statistical pattern approach will be used.

The statistical pattern recognition is an approach of the pattern classification problem, which concentrates on developing decision or classification strategies that form classifiers; i.e. each pattern is represented in terms of d features or measurements and, thus, can be viewed as a point in a d -dimensional space [1]. The objective of a statistical pattern recognition system is to choose features that allow the patterns belonging to different classes to occupy different regions in a d -dimensional feature space. The representation space or feature space is assumed to be effective, if

the patterns from different classes are well separated and if the feature space greatly represents the general properties of the input data. Decision boundaries separate patterns belonging to different classes and they are determined by the specified probability distributions of the patterns belonging to each class. For the case where the training samples used to design a classifier are labeled by their category membership, the procedure is accepted as *supervised*. The opposite case is called *unsupervised* system where the training data is unlabeled.

3.1. Feature Dimension Reduction:

Feature selection involves the derivation of certain features from the input data in order to reduce the amount of data used for recognition and provide discrimination power. Due to the measurement cost and recognition/verification accuracy, the number of features should be kept as small as possible. Less number of selected features makes the system work faster and uses less memory. However, feature extraction methods try to reduce the feature dimensions used in the recognition step. One of the most common used methods in pattern recognition to reduce the feature dimensions is the Principal Component Analysis (PCA) [7]. The advantage of PCA comes from; it reduces the feature space dimension by considering the variance of the input data. In order to obtain the best variance in the data, the data is projected to a subspace (of the image space) which is built by the *eigenvectors* from the data. In that sense, the eigenvalue corresponding to an eigenvector represents the amount of variance that eigenvector handles. The mathematical formulation of PCA is discussed below.

4. Eigenhand Recognition Based on KL-Transformation Method:

The best known linear feature extractor is the *PCA* or Karhunen-LoeÁve (*KL*) expansion that computes the largest eigenvectors of the covariance matrix of the

patterns [7]. As an example, let we have m hand-images, each of size $N \times N$ pixels. Each sample image $f_k(x, y)$ can be expressed in the form of an N^2 -dimensional vector X_k , which constructed by sticking image rows after other (it can also be formed by using columns instead of rows), as follows:

$$X_k = \begin{bmatrix} f_{k(1,1)} \\ f_{k(1,2)} \\ \vdots \\ f_{k(1,N)} \\ f_{k(2,1)} \\ \vdots \\ f_{k(2,N)} \\ \vdots \\ f_{k(N,N)} \end{bmatrix} \quad (13)$$

Where $f_{k(i,j)}$ denotes the $(i, j)^{th}$ element of the k^{th} image.

Let M represents the matrix involves m vectors of the hand-images; i.e.

$$M = \begin{bmatrix} f_{1(1,1)} & f_{2(1,1)} & \cdots & f_{m-1(1,1)} & f_{m(1,1)} \\ f_{1(1,2)} & f_{2(1,2)} & \cdots & f_{m-1(1,2)} & f_{m(1,2)} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ f_{1(1,N)} & f_{2(1,N)} & \cdots & f_{m-1(1,N)} & f_{m(1,N)} \\ f_{1(2,1)} & f_{2(2,1)} & \cdots & f_{m-1(2,1)} & f_{m(2,1)} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ f_{1(2,N)} & f_{2(2,N)} & \cdots & f_{m-1(2,N)} & f_{m(2,N)} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ f_{1(N-1,N)} & f_{2(N-1,N)} & \cdots & f_{m-1(N-1,N)} & f_{m(N-1,N)} \\ f_{1(N,N)} & f_{2(N,N)} & \cdots & f_{m-1(N,N)} & f_{m(N,N)} \end{bmatrix} \quad (14)$$

The covariance matrix of M can now be defined by;

$$C_x = (M - \bar{X})^T (M - \bar{X}) \quad (15)$$

Where: T indicates transposition, and;

$$\bar{X} = \frac{1}{m} \sum_{i=1}^m X_i$$

Since the matrix $(M - \bar{X})$ has the dimensionality $N^2 \times m$, the covariance

matrix will have a dimensionality of $m \times m$. Let e_i and λ_i , $i=1,2,\dots, m$ be the eigenvectors and eigenvalues of C_x . For convenience, it is assumed that the eigenvalues have been arranged in decreasing order, i.e. $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_m$. The matrix whose rows are the eigenvectors of C_x represents the **KL**-transformation matrix, given by;

$$A = \begin{bmatrix} e_{11} & e_{12} & \cdots & \cdots & e_{1m} \\ e_{21} & e_{22} & \cdots & \cdots & e_{2m} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ e_{m1} & e_{m2} & \cdots & \cdots & e_{mm} \end{bmatrix} \quad (16)$$

The **KL**-transformation is simply performed by multiplying the centralized image vectors $(X_i - \bar{X})$ by A to obtain a new image vector; i.e.,

$$Y_i = A (X_i - \bar{X}) \quad (17)$$

5. The Experimental Results:

For the purpose of simplicity, we shall start with as fewer numbers of samples as possible. Let us adopt first only 6-samples of hand images shown in Fig.(8).

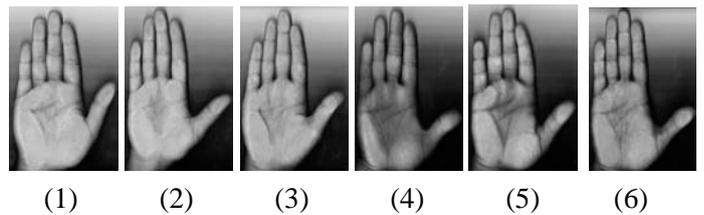


Figure (8): Training set of six hand images, each of 256x256 pixels size.

The average hand's image is shown in Fig.(9).



Figure (9): The average hand of the training set.

Figure (10) represent the mean reduced (each referred as *Eigenhand*) of the training set of the hand's images.

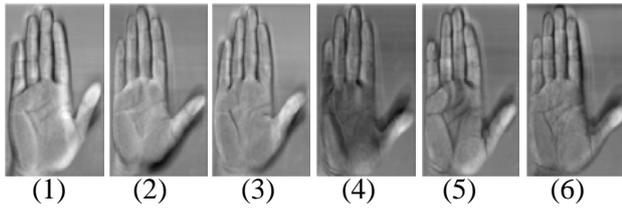


Figure (10): The mean reduced *Eigenhands* of the training set of images.

The computed eigenvalues and eigenvectors are given in Table-1. Note, for

convenience the eigenvalues and eigenvectors elements are approximated to nearest four decimal values.

Let us now see what would happen if one of the above trained images is used as a test image; i.e. the set of the trained image will be increased by inserting a test image.

Table-2, illustrates the computed Eigen values and vectors of the new trained plus test set of images.

Eigenvalues λ 's	V_1	V_2	V_3	V_4	V_5	V_6
1.7595e+008	0.4083	0.4083	0.4083	0.4083	0.4083	0.4083
8.0402e+007	-0.2388	-0.5440	0.3134	0.7186	-0.0978	-0.1513
3.6076e+007	0.0344	-0.2979	0.1715	-0.1924	-0.4915	0.7760
3.1982e+007	0.3392	0.0552	-0.7566	0.4786	-0.2501	0.1336
2.5753e+007	-0.5926	0.6515	0.0681	0.2232	-0.4082	0.0580
-1.4901e-008	-0.5558	-0.1457	-0.3587	0.0334	0.5942	0.4326

Eigenvalues λ 's	V_1	V_2	V_3	V_4	V_5	V_6	V_7
1.9823e+008	-0.3777	-0.3777	-0.4055	-0.3777	-0.3777	-0.3777	-0.3498
8.0827e+007	0.0149	0.0149	-0.6917	0.0149	0.0149	0.0149	0.7214
5.2917e+007	0.1815	0.5112	-0.0830	-0.8063	0.1022	0.1774	-0.0830
3.2134e+007	-0.0801	0.3088	-0.0272	0.0785	0.5289	-0.7816	-0.0272
2.6448e+007	-0.4584	-0.3396	0.4849	-0.3911	0.2264	-0.0071	0.4849
3.1148e-008	-0.6487	0.6159	0.0771	0.1946	-0.3818	0.0657	0.0771
-4.8470e-007	0.4323	0.0763	0.3293	-0.1002	-0.6082	-0.4587	0.3293

As it is obvious, the similarity between the test image (represented by the eigenvector V_7) and the trained set is presented by the 3rd eigenvector V_3 . The similarity test can be performed by utilizing the Minimum-Mean-Distance “MMD” criterion given by [9]:

$$MMD = \text{Min}\left\{ \sum_{i=1}^{m-1} \sum_{k=1}^m |V_{m,k} - V_{i,k}| \right\} \quad (18)$$

Where: “ i ” represents the vector indexing

number, and “ k ” is the vector's elements number. As an example, Table-3 represents

the counted MMD values for the eigenvectors given in Table-2, and by considering different number of vector's elements.

Let us now examine the effects of the noise on the similarity tests between the eigenvectors of the image to be verified and the trained set of images. Figure (11) demonstrates the hand image (shown in

Fig.(8-(3)) with varied amounts of different noise.

Table-3: The counted MMD between the test and trained images.						
No. of adopted elements (in descended order)	$ V_7 - V_1 $	$ V_7 - V_2 $	$ V_7 - V_3 $	$ V_7 - V_4 $	$ V_7 - V_5 $	$ V_7 - V_6 $
6	2.8615	3.3185	1.5441	3.024	3.1683	3.0782
5	2.7932	3.2503	1.4076	2.9558	3.1001	3.01
4	2.0894	2.5464	0.0	2.252	2.3963	2.3062

Table-4: The Eigenvectors of the noisy images								
<i>Eigenvector</i>		<i>Eigenvector elements</i>						
<i>Non noisy image</i>		-0.3498	0.7214	-0.0830	-0.0272	0.4849	0.0771	0.3293
<i>Image with Gaussian noise</i>	$\sigma=7$	-0.3780	-0.6470	-0.1358	-0.0273	0.4297	0.0885	0.4763
	$\sigma=10$	0.3780	0.6579	0.1362	-0.0282	-0.4401	0.0656	0.4550
	$\sigma=12$	0.3780	0.6788	0.1196	-0.0293	-0.4627	0.0436	0.4064
	$\sigma=15$	0.3780	-0.6360	0.1497	-0.0299	0.4793	0.0342	0.4454
<i>Image With Uniform noise</i>	$\sigma=7$	0.3780	0.6207	0.1427	-0.0282	-0.4289	0.1034	0.5060
	$\sigma=10$	0.3780	0.6238	0.1418	-0.0286	-0.4454	0.0969	0.4893
	$\sigma=12$	0.3780	0.6164	0.1458	-0.0301	-0.4571	0.0941	0.4871
	$\sigma=15$	0.3780	-0.6056	0.1551	-0.0310	0.4753	0.0753	0.4835
<i>Image With Impulse Salt-Pepper noise</i>	$\rho_a, \rho_b = 0.03$	0.3780	-0.3032	0.2026	0.0435	0.3906	0.6054	0.4507
	$\rho_a, \rho_b = 0.04$	0.3780	0.1797	0.2145	0.0571	0.0978	0.7147	0.5051
	$\rho_a, \rho_b = 0.05$	0.3780	-0.1114	0.1891	0.0732	0.0407	0.6954	0.5643
	$\rho_a, \rho_b = 0.08$	0.3780	-0.0358	0.0835	-0.1072	0.0031	0.5449	0.7352

Table-5: The counted MMD between the test and trained images.							
No of adopted elements= 5	$V_7 - V_1$	$ V_7 - V_2 $	$ V_7 - V_3 $	$ V_7 - V_4 $	$ V_7 - V_5 $	$ V_7 - V_6 $	<i>Test result</i>
Gaussian $\sigma=7$	2.1389	2.7394	0.5025	2.2388	2.4108	2.4163	Verified
Gaussian $\sigma=10$	2.0892	2.7353	0.4164	2.2751	2.4219	2.4065	Verified
Gaussian $\sigma=12$	1.9897	2.6870	0.2634	2.3159	2.4220	2.3897	Verified
Gaussian $\sigma=15$	2.0881	2.7894	0.4457	2.3450	2.4741	2.4668	Verified
Uniform $\sigma=7$	2.2075	2.7760	0.5900	2.2183	2.4145	2.4486	Verified
Uniform $\sigma=10$	2.1873	2.7733	0.51807	2.2376	2.4339	2.4481	Verified
Uniform $\sigma=12$	2.1945	2.7880	0.5379	2.2469	2.4523	2.4572	Verified
Uniform $\sigma=15$	2.1948	2.8205	0.5596	2.2857	2.4818	2.4617	Verified
Salt-Pepper $\rho_a, \rho_b = 0.03$	1.9436	2.8633	1.7427	2.6700	2.6239	2.9543	Verified
Salt-Pepper $\rho_a, \rho_b = 0.04$	2.1308	2.8756	2.1179	2.4190	2.7961	2.8639	Verified
Salt-Pepper $\rho_a, \rho_b = 0.05$	2.2112	2.7382	2.3794	2.3494	2.7066	2.8110	Unverified
Salt-Pepper $\rho_a, \rho_b = 0.08$	2.4329	2.6256	2.7347	2.3876	2.5465	2.5506	Unverified

Note: The verification test is failed when the amount of noise is increased above $\sigma \geq 30$ for the Gaussian, $\sigma \geq 40$ for the Uniform, and when $\rho_a, \rho_b \geq 0.05$ for the Salt-Pepper noise, as illustrated in Fig. (12).

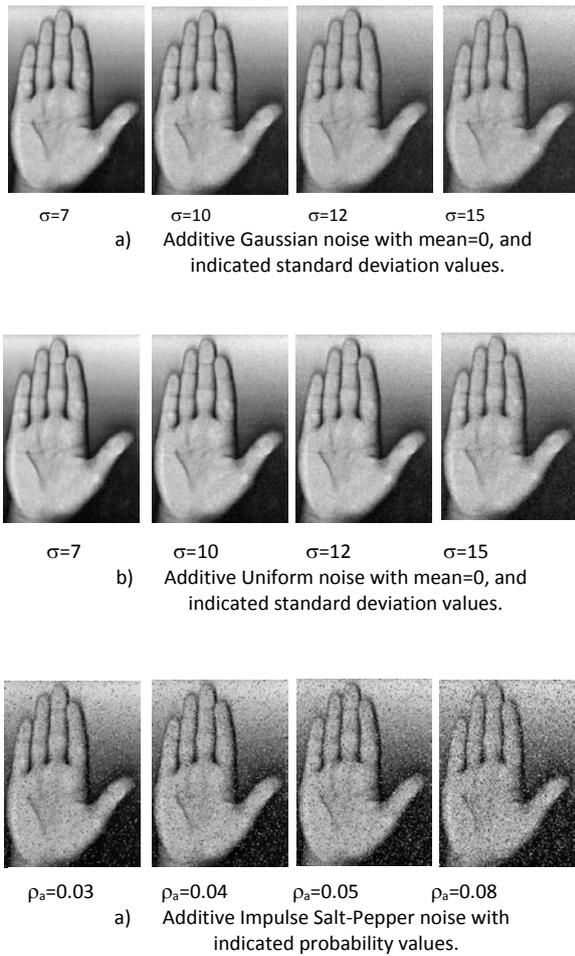


Figure (11): Corrupted images with different amount of different noise.

The noise effects test is illustrated in Figure (12): Plots of the MMD via the noise's amount of noise, indicating the verification condition as a function of the amount of each types of noise. listed as V_7 in Table-2.

The Minimum-Mean-Distance “MMD” between the test and trained set of images,

for varying amount of different noise, are listed in Table-5. The validity of the verifying test of the introduced method is illustrated in Fig.(12) which represent the plots of the MMD values against the noise's amounts (presented by the noise's standard deviations or by the probability density function).

In fact unverified noisy images can be verified by subjecting them to certain suitable filtration method. Figure (13) illustrates selected versions of unverified samples of hand images and their filtrated versions. As is obvious, the first column represents the corrupted version of images by, respectively, Gaussian ($\sigma = 30$), Uniform ($\sigma = 45$), and Salt-Pepper ($\rho_a, \rho_b = 0.1$), while the second column represents the unverified MMD vectors of the corrupted image. The third column represents the smoothed version of images using, respectively, Gaussian filter of size 5×5 , Mean filter of size 5×5 , and Contra-Harmonic filter of size 7×7 , the verified MMD vectors of the smoothed images are shown in the forth column, for the details of the used filters see [20].

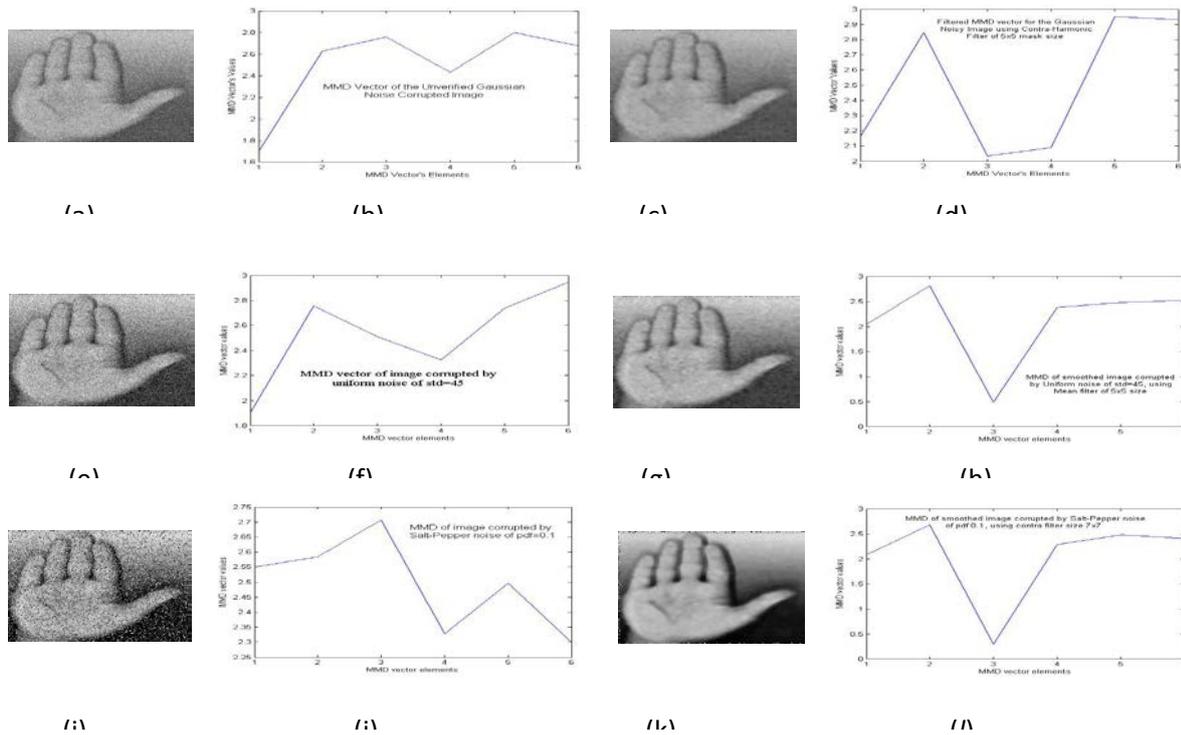


Figure (13): demonstration of the smoothing filtration effects on the verification decision of the introduce eigenhand verification system.

Let us now examine the effects of the rotation on the verification tests between the eigenvectors of the image to be verified and the trained set of images. Figure (14) shows the rotated versions of the hand image (shown in Fig.(8-(3))). The verification test is illustrated in Table-6, by listing the MMD vectors of each rotated image. Image resizing is also studied by supposing the image was moved toward the

camera (i.e. image size is increased). The resizing effects are illustrated in Fig.(15) and Table-7. Let us see what would happen if the object is moved or shifted certain distance. Figure (16) represents the shifted versions of hand images toward the right (the movements are presented by means of number of pixels). Table-8 shows the verification test, presented by the MMD vector.

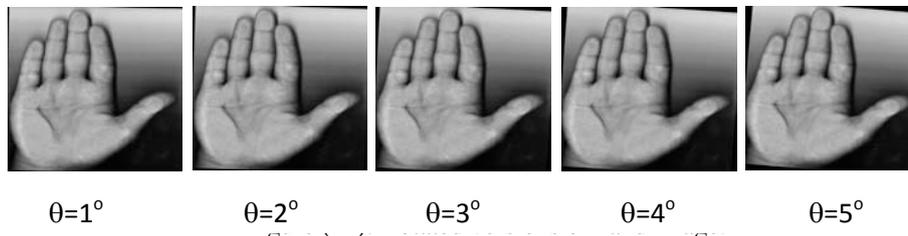


Table-6: The counted MMD vectors between trained and rotated images.

Clockwise rotation angle "θ"	MMD vector's elements						Verification testing Result
	1°	2.1561	2.5781	0.2633	2.2481	2.4878	
2°	2.2391	2.6116	0.5898	2.2334	2.5994	2.3672	Verified
3°	2.3197	2.5972	1.0029	2.3688	2.7108	2.4336	Verified
4°	2.3454	2.4562	1.4944	2.5749	2.7726	2.4826	Verified
5°	2.1086	2.0571	2.7657	2.1752	2.6510	2.9915	Unverified

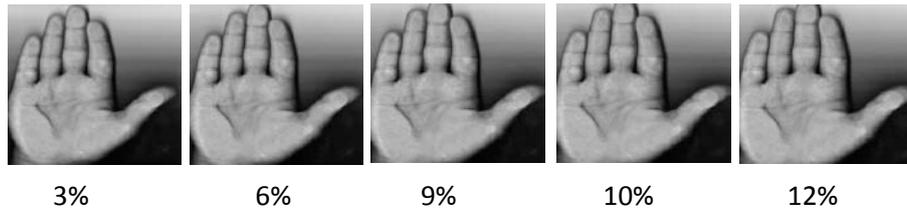


Figure (15): Resized versions of hand image by the shown factor below each.

Table-7: The counted MMD vectors between trained and resized images.

Resize Factor	MMD vector's elements						Verification testing Result
3%	2.1818	2.5798	0.5955	2.169	2.4844	2.428	Verified
6%	2.3228	2.7803	0.7748	2.0816	2.7356	2.6102	Verified
9%	2.1847	2.7021	1.8778	2.0141	3.023	2.7280	Verified
10%	2.0401	2.6018	2.0138	2.0836	3.0051	2.6698	Verified
12%	2.0897	2.4012	2.2883	2.3187	2.7999	2.7392	Unverified

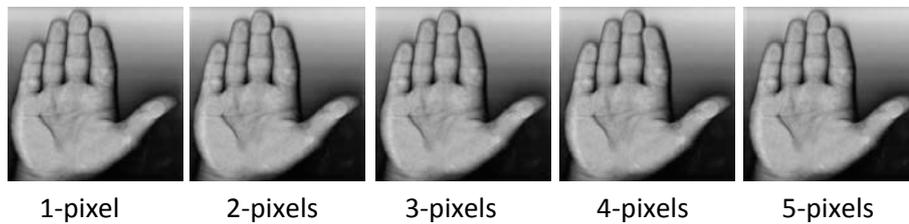


Figure (16): Shifted versions of hand image presented by pixel size, shown below each.

Table-8: The counted MMD vectors between trained and shifted images.

Shift in pixels	MMD vector's elements						Verification testing Result
1	2.0243	2.5842	0.1453	2.3162	2.3833	2.3066	Verified
2	1.9440	2.6011	0.3210	2.3637	2.3615	2.3033	Verified
3	1.8378	2.5975	0.5412	2.4054	2.3266	2.2639	Verified
4	1.6948	2.5745	0.8225	2.4535	2.2773	2.1740	Verified
5	1.5671	2.5198	1.1814	2.5347	2.1978	2.0134	Unverified

Finally, it should be noted that; we have tested our verification system on a set larger samples 25 trained hand images, the results were the same as those achieved on the smaller examined set above. Figure (17) represents the verified MMD vector applied on a set of 25 trained hand images.

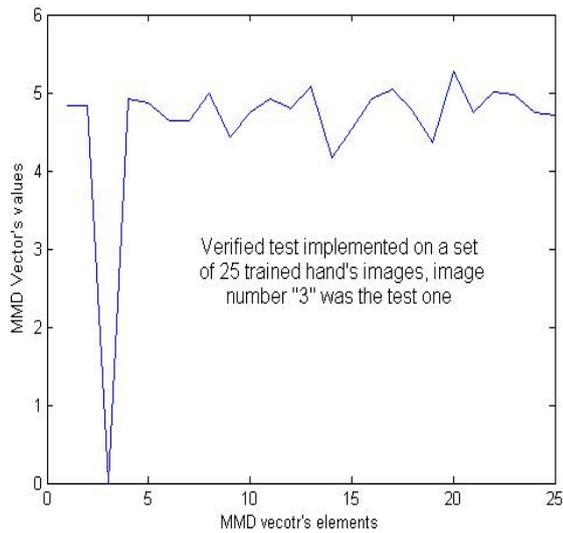


Figure (17): Verification test performed on a set of 25 images

6. Conclusions:

A hand image verification system has been designed and introduced to identify the existence of an examined test image among a set of trained images. Several preprocessing and enhancement techniques have been discussed with the hope to be using them if they were required to improve the system's input images. The effects of noise, bad-illumination, resizing, rotation, and shifting have been studied and illustrated. The illustrated obtained results showed that the presented system is, to some extent, partially invariant toward the studied effects. In case if the test showed unverified result, some suitable manipulations have been suggested to improve the testing results.

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