Off-Line Arabic Signature Recognition Based on Invariant Moments Properties

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Abstract

In this paper, a number of persons were selected to use their signature as a database for the work. Six signatures were taken from each person through two separated period of time using the same pen and paper. The adopted method consists of three main steps. In the first step, the digital image of the signature transformed into contours. After that the main contours were extracted and the noise was rejected. These extracted contours and their dimensions were measured precisely according to their (x) and (y) axis. Second step is the coding step, where the (Chain Code) method was used to code the extracted contour from the first step, converted them into vectors in which they are very easy to deal with. Using length of the vectors were sorted descending by that can be easily used in comparison process. The third (final) step includes application of the (Invariant Moments) method with these chain vectors and the calculated mean of the output for the five signatures taken for each signer and used it as a reference feature for the signer in the recognition process. The signature recognition process completed using the (Minimum Distance) method as a classifier to identify the personal signature.

تمييز التواقيع العربية بالاعتماد على خصائص العزوم الثابتة

الخلاصة

في هذا البحث, تم انتخاب مجموعة من الأشخاص لا على التعيين واستخدام توقيعهم كقاعدة بيانات لعملنا هذا. ولقد تم اخذ أكثر من توقيع من كل واحد منهم (6 تواقيع لكل شخص) وخلال فترتين زمنيتين متباعدتين مستخدمين نفس النوع من القلم و الورق. في هذه الطريقة تم تحويل صورة التوقيع الرقمية إلى مخططات (Contours) واستخلاص المؤثرة منها وحذف الأشكال الناتجة من الضوضاء، ومن ثم عزلت هذه المخططات وحددت أبعادها بدقة على المحورين السيني و الصادي. الخطوة الثانية في هذه الطريقة هي عملية تشفير المخططات المعزولة من الخطوة الأولى. استخدمت طريقة التشفير التسلسلي (Chain Code) لتحويل هذه المخططات إلى متجهات حيث تتصف هذه المتجهات بسهولة التعامل معها. بعد ذلك رتبت هذه المتجهات ترتيباً تنازلياً وحسب طول المتجه وذلك لغرض إجراء عملية المقارنة وبشكل بسيط. الخطوة الأخير تتضمن استخلاص الصفات المهمة من صورة التوقيع بتطبيق طريقة العزوم الثابتة (Invariant Moment) على هذه المتجهات واخذ معدل التواقيع الخمسة لكل مشترك في الدراسة لتقليل الخطاء الإحصائي الناتج واستخدامها كمعلومات مرجعية لهؤلاء الأشخاص عند إجراء عملية التعريف، حيث تجري عملية التعريف للتواقيع غير المعرفة باستخدام طريقة تصنيف الأقل مسافة (Minimum Distance) لتحديد التقارب و التعرف على التوقيع.

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Introduction

Pattern Recognition can be defined as; "the categorization of input data into identifiable classes via the extraction of significant features or attributes of the data from a background of irrelevant detail" [1]. The field of pattern recognition includes a number of applications that has been implemented and studied, i.e., radar detection, speech recognition, finger print identification and handwritten characters recognition. Handwritten signatures are a special case of handwriting subject to intra-personal variation and inter-personal differences. Human signatures provide secure means for authentication and authorisation in legal and banking documents; therefore the need of research in efficient automatic solutions for the involved signature recognition and verification problems has increased. Signatures are most legal and common means for individual's identity verification. People are familiar with the use of signatures in their daily life. Automatic signature recognition has many applications including credit card validation, security systems, cheques, contracts, etc. There are two types of systems in this field, signature verification systems and signature recognition systems. A signature verification system just decides whether a given signature belongs to a claimed writer or not. A signature recognition system, on the other hand, has to decide a given signature belongs to which one of a certain number of writers [2]. The design of any signature recognition system requires the solutions for four types of problems: data acquisition, preprocessing, feature extraction, and comparison process. Automatic signature recognition requires a representation of the handwritten signature that is suitable for computer processing. There are basically two approaches to obtain such a representation: Dynamic (on-line) approach and Static (off-line) approach. Dynamic systems use a digitizer or an electronic pen to generate signals; static systems produce an image of a signature with the help of a camera or page scanner. In the first approach, the signature is considered as one or several signals varying with time, u (t), gives a representation of the written signature. In the second approach, the signature written on paper appears as a 2-D image which can be picked up by optical means. This paper focuses on the analysis of the static (off-line) features of a handwritten personal signature. In this paper we deal with an off-line Arabic cursive signature recognition technique, where the signature is capture and presented to the user in the format of image only. We use various image processing techniques to extract the parameters of personal signatures and recognition the signature based on these parameters. In processing step, the raw data are preprocessed to remove noise information, to filter the significant images, and to validate the acquisition. The next step is referred to as the feature extraction process. Specific discriminating functions or parameters are computed from the filtered input data and are used to represent the signature. Prior to performing

comparisons, a signature reference set must be generated for each user of the system, which is registered in the reference database during the enrollment process. At the comparison stage, the features of the tested signature just collected and then compared to all the references of the database. Finally a decision process evaluates the comparison criteria with respect to specific threshold and the signature is either accepted or rejected [3]. The rest of paper is organized as follows. After this introduction, Section (2) presents specific descriptions of (Invariant Moments properties). The signature database and pre-processing procedures for signature recognition; noise removal from signature image, contour extraction and chain coding are described in section (3). Section (4), will be directed to demonstrate the experimental results, and recognition phase. Finally, conclusions and remarks are given in section (5).

Invariant Moments

The theory of moments provides an interesting and sometimes useful alternative for series expansions for representing objects and shapes. The use of moments for image analysis is straightforward if we consider a binary or gray level image segment as a two-dimensional density distribution function. [4]. Various types of moment's theory have been used to recognize image patterns in a number of applications. Moment descriptors (moment invariants) are used in many pattern recognition applications. The idea of using moments in shape recognition gained prominence in 1961, when Hu derived a set of invariants using the theory of algebraic invariants [5]. Moment invariants are properties of connected regions in binary images that are invariant to translation, rotation and scaling. They can be easily calculated from region properties and they are very useful in performing shape classification and part recognition. One of the techniques for generating invariants in terms of algebraic moment was originally proposed by Hu [5] [4]. The algebraic moment of the characteristic function f(x, y) is defined to be:

$$M_{pq} = \int_x \int_y x^p y^q f(x,y)\, d_x \; d_y \quad ..... \quad (1)$$

Where: p, q=0, 1, 2,……

This can be approximated in discrete form by:

$$M_{pq} = \sum_x \sum_y x^p y^q f(x,y) \quad ..... \quad (2)$$

A geometric figure can be uniquely determined by its algebraic moment. Therefore, instead of looking for invariants of moments, only invariants of low order moments are used in practical applications. Moment invariants are usually specified in terms of centralized moment. Here, the moment is measured with respect to the “center of mass”, (x’, y’). The central moment, μ, with respect to the centroid, and the normalized central moment, η, are calculated as:

$$M_{pq} = \sum_x \sum_y (x - x')^p (y - y')^q a_{xy} \quad .....(3)$$

$$\eta_{pq} = \frac{\mu_{pq}}{(\mu_{00})^{\lambda}}$$

Where:

$$\lambda = \frac{(p+q)}{2} + 1,\ (p+q) > 2$$

The moment invariants used in our work are computed using the equations given in table (1-B) [6], for all signatures in this work.

The Proposed Method:

In this section the procedures for identifying the persons from their personal signature will be presented. Figure (1); show the block diagram of the Proposed Signature Recognition Method. The implementation of the suggested technique will mainly be consisted of enrollment phase and recognition phase.

Enrollment Phase:

We used reference image database containing (84) different Arabic cursive signatures signed by (14) different persons. In enrollment phase the specimens (i.e. signatures) of each signer are fed to the computer by using page scanner. Then each specimen is handled separately, where if there is any noise in the signature image it will be eliminated automatically, each image is binarized, the body of the signature is clipped from its surroundings, all these processes represent the preprocessing stage of the suggested system. Then, the values of the considered features (i.e. Invariant Moment) are extracted and selected to describe each specimen. Finally, these sets of features are stored in reference database. By saving the feature vectors of all signatures samples in the reference database, the enrollment phase will be finished. All these processes will be discussed in the next sections.

Pre-Processing Procedures for Signature Recognition:

Any image processing application suffers from noise like touching line segments, isolated pixels and smeared images. This noise may cause severe distortions in the digital image and hence ambiguous features and a correspondingly poor recognition rate. Therefore, a preprocessor is used to remove noise and to make signatures standard and ready for feature extraction. Preprocessing techniques eliminate much of the variability of signature data. Indeed, a perfect preprocessing system would make the signatures of the same person uniform, removing as much noise as possible and preparing the resulting data for feature extraction and classification, thus improving the performance of the recognition technique. The primary concern is to keep the main characteristics of the signatures unchanged. The preprocessing step is applied both in enrollment and testing phases.

Signatures Database

Because there was no standard database for personal signatures, we gathered a database. This reference database for Arabic personal signatures consists of (84) different signatures belong to (14) persons have been adopted and used to perform the identification processes. The chosen persons have given a pen and a blank sheet of paper divided to (6) rectangles in each column, they have asked to put

their personal's signatures at certain positions. The identifier was trained by using (5th) specimens for each signer. The (6th) signature was used for test phase. These personal signatures database have been preprocessed before recognition phase. Training process is performed, by computing the invariant moment values for each signature,. Then, the extracted moment values were tabulated in reference database, Table (4), to be used by the identifier later. However, mean value is used as statistical parameters in our proposed recognition method. Figure (2) shows some samples of gathered database signatures for different signers.

Signature Image Acquisition:

The first step in the signature recognition process is signature image acquisition. It consists of utilizing the page scanner device to convert the signature image into a numerical representation, which is suitable for a digital computer. A resolution of (300 dpi (dots per inch)) with (8 bits/pixels), is employed in the work. Each signature image is stored as BMP file. Photographic camera or video camera may be used instead of a page scanner.

Signature Image Binarization:

Binary images are often created from gray-scale images via a threshold operation [7]. In this step, the signature image is converted from gray image to a binary image, whose pixels' values are the set of one's or zero's according to brightness of the points of the signature image. To binarize the signature image, a threshold value is chosen where each pixel value is compared with this threshold. In the proposed technique, the threshold value is computed for each signature image entered to the system by computing its histogram. From this histogram the valley point is computed which will be considered as the threshold value for the corresponding signature image. Then all pixels' values of the signature image that are greater than or equal to the threshold value will be zeros [background], otherwise the pixel values will be ones [object] [foreground] [8]. Figure (3) shows the output of the binarization process.

Noise Removal from the Signature Image:

Before any further processing takes place, a noise reduction filter is applied to the binary image. The goal of applying this step is to eliminate the single white pixels on black background or single black pixels on white background. In other words, the goal is to remove any isolated pixel that does not belong to foreground image but it exists in the background image and it affects the stage of feature selection. To remove this pixel, the mask of (3x3) is used, see figure (4), and the following decision rule is applied to the signature image: if the (8) neighbors of a tested pixel have the same value but the center of the (8) neighbors have a different value then the color of the central pixel should be inverted. This method is called a singular point removing [2]. The algorithm below shows the decision rule.

Algorithm (1): Noise Removal from Signature Image:

Input: Image matrix

Output: Image matrix
For all pixels in the image matrix do
Begin
R=p[2]+p[3]+p[4]+p[5]+p[6]+p[7]+p[8]+p[9]
If R=0 then p[1]=0
Else If R=8 then p[1] =1
End

Determination of Signature Image Size:

The signature image is scanned from right to left, and top to down. So when the signature image is captured, there is a space surrounding it. This space should be eliminated by scanning the image from outside to inside margins; this scanning should be done to all sides of the signature image and will be stopped when the first pixel of object is detected, as shown in figure (5). The space (background) of the image that is surrounding the signature (object) is eliminated. The advantage of signature area cropping is to reduce the time and detect the signature image that the program works on. In order to define the best size of a signature it is desirable to surround it by a box that fit it without any gap of rows or columns. Thus the signature size may be defined by:

$$X_D = X_{max} - X_{min} \quad \ldots\ldots \quad (4)$$

$$Y_D = Y_{max} - Y_{min} \quad \ldots\ldots \quad (5)$$

Where: (X_D) and (Y_D), represents the horizontal and vertical dimensions of a signature respectively.

Contour Information Extraction:

Contour is one of the most fundamental information after image segmentation. In this stage, a set of border pixel positions are extracted and recorded in an appropriate data structure. To detect contour information for signature image we use a (3x3) template (T), as shown in figure (6) to operate on a binary signature image f(x, y), whose character regions have value one and background points have value zero [9][10].

Contour Points Detection:

Pixels in f(x, y) (signature's image) are classified into three categories (interior, noise and contour points) which are defined as follows:

1) Interior Point: when all of the (8) - neighbors of point (P) equal (1), then the pixel is defined as an interior point. The illustrations of interior point are shown in figure (7).

2) Noise Point: when n_i, $n_{i+1}, \ldots, n_{(i+m) \bmod (8)}$ is (1), where ($0 \le i \le 7$), and ($m \ge 1$), then (n_i, $n_{i+1}, \ldots, n_{(i+m) \bmod (8)}$) is defined as a set of consecutive points. If the neighborhood combinations satisfy the following two criteria, then the pixel is a noise point:

A) There does not exist any consecutive points as shown in figures (8-a) and (8-b).

B) The number of sets of consecutive points equals two and there does not exist a simple cycle as shown in figure (8-c).

3) Contour Point: all points of the binary signature image except interior and noise points. Some contour points are shown in figure (9).

The result of contour points are stored in a new image, where the contour point is set to one and noise and interior points is set to zero. When

a noise point is detected, its pixel value in the original image is set to zero and the process of contour point detection for the neighboring lines encompassed by the template has to be redone. Figure (10), show example for signature image after contouring.

Contours' Signature Following and Isolation:

Chain codes are used to represent a boundary by a connected sequence of straight-line segment of specified length and direction. Typically, this representation is based on (8-connectivity) and (4-connectivity) of the segment. The direction of each segment is coded by using a scheme shown in figure (11). After contours are extracted, we trace the contour of the same region by using the freeman-chain code [5] [11]. The exterior and interior boundaries are traced by the clockwise direction.

When we code certain signature into vector form (by using chain coding technique), we use the "0" codes as separator between different segments of the processed signature. This coding form making the isolation and extraction process easy; i.e. each contour segment can be presented in an isolate vector, prepared for further identification and recognition processes. As shown in figure (12).

After extracting the contours founded in the signature image, four parameters will be evaluated that represent width, height, length and start point of each contour as listed in table (2) respectively. For the purpose of comparison, the contour segments of each signature are arranged in the form: of the longest to the shortest form relative to the contour's length, as tabulated in table (3).

Contour's Signature Normalization Process:

By this normalization process we transform the image coordinates (X, Y) into normalized set (X_n,Y_n), so that the new set of coordinates satisfies a set of conditions, which we call it the normalization criteria. Therefore, (X_n, Y_n) can be considered as a standard version of the original coordinates (X, Y). The purpose of this operation is to keep the domain of image coordinates fixed and irrelevant to the original size. In our normalization procedure, the signature contours have normalized with respect to the larger (dominant) boundary; i.e. the larger boundary points have given coordinates scaled between (–1) to (1), all other existed counters then measured with respect to that scaling scheme figure (13). The following relationships have adopted to perform this normalization process:

$$X_n = 2 \times \left(\frac{x - \min x}{\max x - \min x}\right) - 1 \quad \ldots. \quad (6)$$

$$Y_n = 2 \times \left(\frac{y - \min y}{\max y - \min y}\right) - 1 \quad \ldots. \quad (7)$$

Where: (min x), (max x), represent the minimum and maximum of the (X-axis) of the first contour, and (min y), (max y), represent the minimum and maximum of the (Y-axis) of the first contour, respectively.

Calculating Invariant Moments:

The choice of a powerful set of features is crucial in signatures recognition techniques. Feature extraction plays a very important role in all pattern recognition systems. Feature extraction is the process of

extracting useful information from the signature image which is used for solving an application problem and reducing the amount of image data. The signature image that passed through image pre-processing is fed to the feature extraction stage to compute the feature information for the signature image. The features are computed and calculated for each signature image. Feature vectors are generated using invariant moments properties. The invariant moments used in this paper are computed using the equations given in table (1) for all signatures. For this purpose, we use five signature images for each person is signing in two different times. Then, we produced five different sets of feature vectors for every signature where each set consisted of seven invariant moments values listed in table (1). Then, the extracted invariant moment's values were tabulated and stored in reference database, to be used by the identifier later. Some samples of features vector sets for Ahmed's signature specimens is shown in table (4).

However, mean value is used as statistical parameters in our recognition system. Table (5) presents the mean of the invariant moments for various orders to Ahmed's signature for different contours.

In order to determine which moment's order gives the better similarity for various shapes of the same personal signature, it can be conclude from table (6) which presents the invariant moment for various orders to Ahmed's signature for five samples of the first contour and see the figure (14), that the first moment order and second moment order are the favorite.

In order to determine the best features (moments order), which used for the purpose of recognition between different signers. We can conclude from figure (15), which represents the relationship between logarithm moments value (the mean of each invariant moment's) and invariant moment orders of the first contour for different signers. It can be seen that the moments of orders two and five are the best features that can be used for identification. Moment of order two seems to be very useful for identification because it reflects no significant difference between the different samples of a signature and secondly the high difference value that reflect for different signature of signers. For moment of order five it seems that this order gives higher difference and therefore it has no not the better performance.

Testing Phase:

After applying the complete preprocessing and feature extraction stages, each personal signature is now represented as an ordered list of features vector sets (consisted of seventh invariant moment's features). The proposed technique now is able to recognize any unknown signature if the signer is in the original reference database. The personal signature recognition is the process of finding the identification of the signature owner. In other words, the recognition process classifies a given signature sample as belonging to one of the known writers in the database. During

the recognition phase a given signature is compared with all stored signatures (database) to retrieve the most similar one to the test signature according to some similarity or distance measure. In this phase most of the operations mentioned in features preparing phase (Enrollment Phase) are performed upon the new unknown signature sample, whose ID has to be recognized. The matching test and decision task then are performed by utilizing the minimum distance classifier mechanism, in which the identification is based on adopting the reference class whose features has the closest distance compared with the features of the previously created Database. The classification processes will be given down. Different methods to compare pairs of ordered lists of features are available in reference [12]. The objective of a signature recognition machine is to identify signer from his signature. Euclidean minimum distance metric has been used in this paper to perform the desired identification, as follows: Let *C* be the features vector representing the test signature. The components of *C* are the values of the set of "invariant moments" features determined by the method described earlier. Let *T* be the reference features vector. The determination of *T* is based on an enrollment set of known signatures. The measure of closeness between the test signature and the reference database signatures can be performed by utilizing the Euclidean minimum distance metric [13] [14], given by:

$$D_{(C,T)} = \frac{\sqrt{\sum_{i=1}^{n} (C_i - T_i)^2}}{n} \quad \text{..... (8)}$$

Where *n* is the number of features, C_i is the value of the ith feature in the feature's vector *C*, T_i is the ith feature of the reference vector *T* as computed from a set of enrollment signatures. The smallest value of $D(_{C,\ T})$, the greater the similarity between *C* and *T*, and therefore between the test signature represented by *C* and the reference signature *T*. Therefore, the test signature represented by *C* belongs to the same class to which the reference signature (represented by *T*) belongs.

Matching Results:

In this paper we propose a simple technique based on invariant moments properties. A prototype recognition technique has been implemented and tested using a Personal Computer powered by Pentium 4 (2.4 GHz) and 1 GHz of RAM with Microsoft Windows XP (SP2). In this work, (70) signature images were used in training phase, while the remaining (14) signature images were used for testing purposes. According to the above analysis, when the proposed technique is asked to decide whether an unknown signature image belongs to a particular person in the database or not, the following steps are followed:

1) Acquisition Stage: The unknown signature image is entered to the system. The test signature image is read with the help of digitizing equipment such as a page scanner.

2) Preprocessing Stage: The unknown signature image passes through the pre-processing stages, which includes,

convert the signature image into binary image, remove any isolated noise pixel that does not belong to foreground signature image, eliminating the space of the image that is surrounding the signature body, contour points detection of the test signature, contours' signature tracing and isolation by using chain coding technique.

3) Features Extraction Stage: In this step, seven invariant moments are computed for an unknown signature.

4) Classification and Recognition Stage: To classify an unknown person from its signature image, Euclidean distance measure is used to evaluate the differences between the features vector of the unknown signature image with the reference features vector sets preserved in the Database. The unknown image then assigned as to belong to certain person depending on the minimum distance obtained from the comparison. Moreover, if two different samples were processed by our technique then it is possible to identify if both the samples belong to the same person or not. However, the decision may be taken according to the degree of similarity between the compared signature samples. In this case, a threshold value should be decided to differentiate between true or false decision (i.e. true means same person, while false indicating different persons). Table (7), shows the signature recognition results achieved by using the (14) tested signatures. For each person, (6) signature images were chosen, (5) signatures of them used as references database. The sixth signature used for purpose testing stage. The results in table (7) it's obtained from implementation of the employed method and utilizing the Euclidean minimum distance criterion (equation 8).

A strategy which used to representing a different weight for each invariant moments order, as follows: Moments of order two and five take the larger weight *(2)*, moments of order three, four and six take the weight of order *(1)*; moments of order one and seven take the lowest weight *(0.5)*. Thus the total weight will be *(8)*. This strategy was adopted in order to give the significant moments order their corresponding weights, while for the different contours, the first contour take *(50%)* of the recognition result, while the other contours take the sharing the other *(50%)* of the result value. Utilizing the minimum distance classifier the similarity is calculated for each contour in the personal signature.

However, the designed technique was not able to recognize all the signers that should be accepted due to several reasons mainly because the shape of signature of some signers is very similar to other signatures. The program could not recognize three signatures from the original data base signatures.

Conclusions and Remarks:

In this paper, a technique for off-line Arabic cursive signature recognition based on (Invariant Moments Properties) has been proposed. Recognition process starts by using a number of signer's specimens to generate the database of the signatures characteristic that can be used for recognition. The proposed

method used Euclidean minimum distance criterion for comparing features. The proposed method in this paper, gives acceptable results in a simple way. The following points can summarize briefly the conclusion of this work:

1) The number of contours may be different from personal signature to another. This feature can be used in identification process as a first step in signature recognition stage.

2) Representing signature image by using chain coding method has several advantages which are as follows:

a) It is a compact coding technique.

b) It is a general application, meaning that it can be applied for any planer shape.

c) It is simple, that can be used to code the image straightforward and fast; most of them can be executed in fractions of second on commercially available equipment.

d) The real reason for using chain code in our work for getting exactly size of the contour and these leads, for exactly size of the signature.

e) The operation of extracting contours and coded it by chain code is very active to remove all noise in template.

f) The chain code is translation invariant.

g) The chain code can be used to compute many shape features, such as the perimeter and area.

h) Chain codes are invariant to boundary size and orientation.

i) Chain codes provide a good compression of boundary description.

j) Representing each signature image by using chain coding technique is very useful to isolation the different contours from the input signature image.

3) From table (5) and figure (14), it can be see that the moments order of the first contour from order (1st - 7th) were the biggest comparing with the other contours belong to the same signature. This is being case; the first contour is the biggest one that represents nearly all the signature area. Consequently, this contour will be used essentially in signature identification process.

4) The moments of order (2 and 5) gives better results for identification process.

5) The time required to train the signature recognition stages depends on the number of persons, number of signature images and the used algorithm.

6) The recognition probability of the proposed technique increases when the features of different signature image taken from the same signer are close to each other.

7) Despite the variation in the used signature, some signatures from different signers can be close enough to each other so that the technique may not make the right decision in recognizing them.

8) Generally, the failure to recognize a signature was due to high similarity between two signatures. Recognition ability of the proposed technique can be increased by using additional features (such as; signature height, image area, maximum vertical projection, maximum horizontal projection) in the input data set.

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Table (1): (A) Formulas Used For Specific Central Moments, and (B) List of the Derived Invariant Moments.

(A) Central Moments	(B) Derived Invariant Moments
$\mu_{00}=m_{00}$	$I_1=\eta_{20} + \eta_{02}$
$\mu_{10}=0$	$I_2=(\eta_{20} -\eta_{02})^2+4\eta_{11}^2$
$\mu_{01}=0$	$I_3=(\eta_{30} - 3\eta_{12})^2+ (3\eta_{21}-\eta_{03})^2$
$\mu_{20}= m_{20}-x'm_{00}$	$I_4=(\eta_{30} + \eta_{12})^2+ (\eta_{21}-\eta_{03})^2$
$\mu_{02}= m_{02}- y'm_{01}$	$I_5=(\eta_{30} - 3\eta_{12}) (\eta_{30} + \eta_{12})^2((\eta_{30} + \eta_{12})^2 -3(\eta_{21} + \eta_{03})^2) + (3\eta_{21} - \eta_{03}) (\eta_{21} + \eta_{03})(3 (\eta_{30} + \eta_{12})^2-(\eta_{21} + \eta_{03})^2)$
$\mu_{11}= m_{11}- y'm_{10}$	$I_6=(\eta_{20} - \eta_{02}) ((\eta_{30} + \eta_{12})^2- (\eta_{21} + \eta_{03})^2)+ 4\eta_{11} (\eta_{30} + \eta_{21})(\eta_{21}+ \eta_{03})$
$\mu_{30}= m_{30}-3x'm_{20} + 2x'm_{10}$	$I_7=(3\eta_{12} - \eta_{30}) (\eta_{30} + \eta_{12})((3\eta_{30} \eta_{12}) - 3(\eta_{21} +\eta_{03})^2) + (3\eta_{21}- \eta_{03}) (\eta_{21} + \eta_{03})((3\eta_{30} \eta_{12})^2 -(\eta_{21} + \eta_{03})^2)$

Table (2): The Extracted Parameters of Each Contour in Personal Signature.

Number of contours	Width = (MaxX- MinX)		Height = (MaxY- MinY)		Length of vector	Start point of the contour	
	Max. X	Min. X	Max. Y	Min. Y		X	Y
Ahmed's Signature	*178*	*2*	*160*	*3*	*1457*	*178*	*48*
Contour 1	*178*	*2*	*160*	*3*	*1212*	*178*	*48*
Contour 2	*171*	*84*	*113*	*66*	*185*	*171*	*66*
Contour 3	*50*	*16*	*79*	*11*	*89*	*50*	*11*
Contour 4	*66*	*29*	*90*	*78*	*132*	*66*	*78*

Table (3): The Arrangement of the Contours for Each Personal Signature.

Before arrangement		After arrangement	
Contour 1	*1212*	*Contour 1*	*1212*
Contour 2	*185*	*Contour 2*	*185*
Contour 3	*89*	*Contour 3*	*132*
Contour 4	*132*	*Contour 4*	*89*

Table (4): Presents the Invariant Moments for Various Orders to Ahmed's Signature for Different Contours.

Personal's Signature	Contour's Number	$(I.M.)_1$	$(I.M.)_2$	$(I.M.)_3$	$(I.M.)_4$	$(I.M.)_5$	$(I.M.)_6$	$(I.M.)_7$
Signature 1	*1*	*3.215 E-04*	*6.698 E-08*	*4.026 E-12*	*8.516 E-12*	*2.175 E-22*	*4.812 E-15*	*6.841 E-23*
	2	*6.195 E-05*	*2.251 E-09*	*4.324 E-14*	*8.205 E-13*	*3.299 E-28*	*2.118 E-20*	*9.004 E-31*
	3	*1.247 E-05*	*2.115 E-09*	*5.835 E-16*	*9.232 E-17*	*2.671 E-31*	*2.858 E-18*	*4.360 E-32*
	4	*4.124 E-05*	*5.947 E-10*	*1.0588 E-15*	*2.446 E-16*	*7.211 E-22*	*3.115 E-20*	*1.886 E-30*
Signature 2	*1*	*3.554 E-04*	*7.123 E-08*	*2.698 E-11*	*1.603 E-13*	*2.591 E-22*	*5.237 E-15*	*8.128 E-23*
	2	*6.466 E-05*	*2.996 E-09*	*1.654 E-13*	*1.687 E-14*	*3.368 E-30*	*3.122 E-19*	*3.715 E-30*
	3	*2.358 E-05*	*5.049 E-10*	*2.654 E-15*	*1.098 E-16*	*7.244 E-32*	*1.951 E-20*	*2.651 E-30*
	4	*3.677 E-05*	*6.115 E-10*	*4.654 E-15*	*6.123 E-17*	*1.167 E-30*	*2.880 E-20*	*4.332 E-30*

Table (5): Mean of the Invariant Moments for Various Orders to Ahmed's Signature for Different Contours.

Personal's Signature	Contour's Number	$(I.M.)_1$	$(I.M.)_2$	$(I.M.)_3$	$(I.M.)_4$	$(I.M.)_5$	$(I.M.)_6$	$(I.M.)_7$
Ahmed's Signature	*1*	*3.085 E-04*	*7.268 E-08*	*6.060 E-12*	*7.731 E-13*	*7.173 E-23*	*3.581 E-15*	*5.840 E-24*
	2	*3.119 E-05*	*1.312 E-09*	*1.567 E-13*	*2.589 E-14*	*5.443 E-29*	*3.113 E-19*	*7.467 E-30*
	3	*2.689 E-05*	*3.445 E-10*	*8.123 E-16*	*5.112 E-17*	*2.789 E-31*	*2.145 E-21*	*2.665 E-32*
	4	*2.342 E-05*	*6.997 E-09*	*2.564 E-14*	*3.442 E-16*	*4.765 E-28*	*1.997 E-20*	*2.115 E-30*

Table (6): The Invariant Moments for Various Orders of the First Contour to Ahmed's Signature for Five Samples.

Personal's Signature	Contour's Number	$(I.M.)_1$	$(I.M.)_2$	$(I.M.)_3$	$(I.M.)_4$	$(I.M.)_5$	$(I.M.)_6$	$(I.M.)_7$
Signature 1	*1*	*3.215 E-04*	*6.698 E-08*	*4.026 E-12*	*8.516 E-12*	*2.175 E-22*	*4.812 E-15*	*6.841 E-23*
Signature 2	*1*	*3.554 E-04*	*7.123 E-08*	*2.698 E-11*	*1.603 E-13*	*2.591 E-22*	*5.237 E-15*	*8.128 E-23*
Signature 3	*1*	*2.211 E-04*	*5.798 E-08*	*2.774 E-12*	*1.123 E-12*	*7.239 E-23*	*5.112 E-14*	*4.089 E-23*
Signature 4	*1*	*3.623 E-04*	*5.451 E-08*	*1.667 E-11*	*1.811 E-13*	*3.556 E-22*	*6.277 E-15*	*2.241 E-22*
Signature 5	*1*	*2.111 E-04*	*6.404 E-08*	*2.987 E-12*	*1.166 E-12*	*3.788 E-23*	*3.792 E-13*	*2.989 E-21*

Table (7): Presents the Success or Fail of Signature Recognition for Each Class (for Each Tested Signature).

Class Number	ID Class	Result of the Trained Signature	Result of Tested Signature	Success
1	*AHMED*	*PASS*	*PASS*	*TRUE*
2	*RASSOUL*	*PASS*	*PASS*	*TRUE*
3	*HAIDAR*	*PASS*	*FAILED*	*FALSE*
4	*FALEH*	*PASS*	*PASS*	*TRUE*
5	*MAZEN*	*PASS*	*PASS*	*TRUE*
6	*RAAD*	*PASS*	*PASS*	*TRUE*
7	*HASSEN*	*PASS*	*FAILED*	*FALSE*
8	*Ali*	*PASS*	*PASS*	*TRUE*
9	*SAAD*	*PASS*	*PASS*	*TRUE*
10	*MOHAMMAD*	*PASS*	*PASS*	*TRUE*
11	*SALAH*	*PASS*	*PASS*	*TRUE*
12	*NABEEL*	*PASS*	*PASS*	*TRUE*
13	*HAMEED*	*PASS*	*FAILED*	*FALSE*
14	*YASSER*	*PASS*	*PASS*	*TRUE*

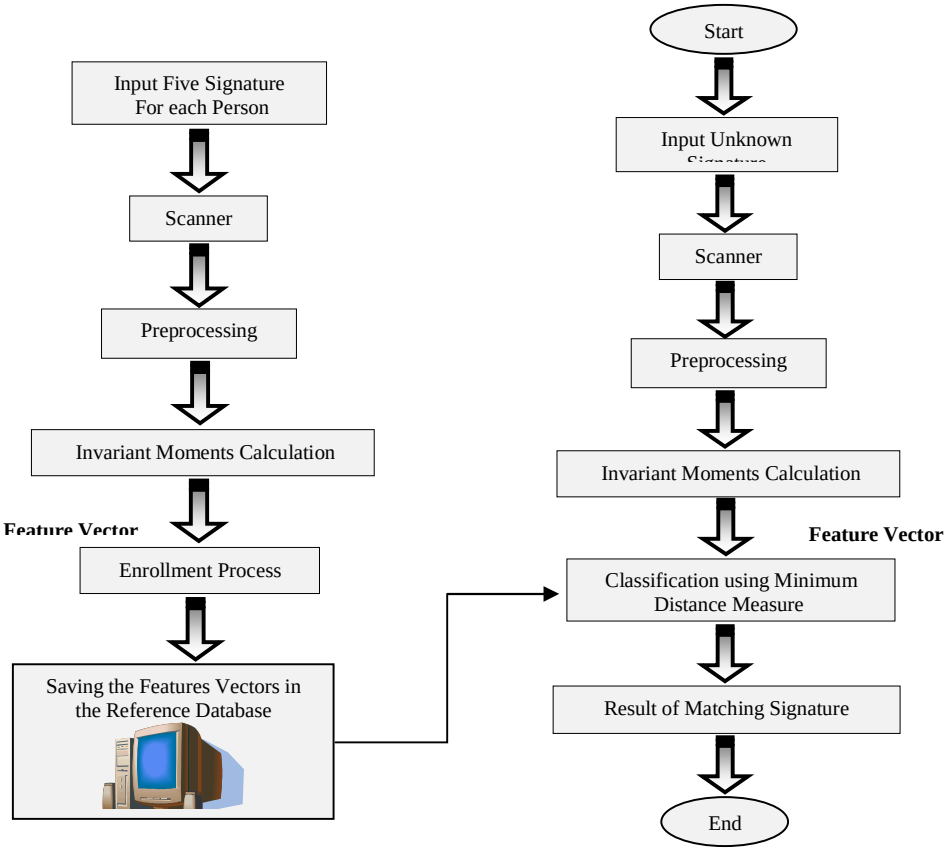


Figure (1): Block Diagram of the Off-Line Arabic Signature Recognition Method.

Figure (2): Some Sample Training Personal Signatures Used in the Experiments.

(A) Input Captured Signature Image (B) Binarized Signature Image

Figure (3): Binarization Process for Signature Image.

P9 (x-1, y-1)	P2 (x-1, y)	P3 (x-1, y+1)
P8 (x, y-1)	P1 (x, y)	P4 (x, y+1)
P7 (x+1, y-1)	P6 (x+1, y)	P5 (x+1, y+1)

Figure (4): Designations of the Nine Pixels in (3x3) Window around the Pixel

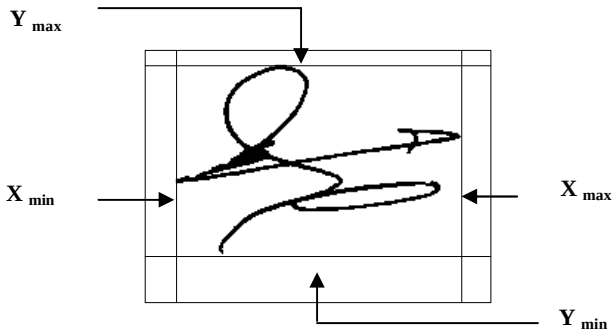


Figure (5): Signature Body

N3	N2	N1
N4	p	N0
N5	N6	N7

Figure (6):8-Connected Neighbors of the Point (P).

1	1	1
1	P	1
1	1	1

(A)

1	1	0
1	P	1
1	1	0

(B)

0	1	0
1	P	1
0	1	0

(C)

Figure (7): Examples of Interior Point.

1	0	0
0	P	1
1	0	0

(A)

0	0	0
1	P	1
0	0	0

(B)

1	0	0
1	P	1
1	0	1

(C)

Figure (8): Examples of Noise Point.

1	1	1
1	P	0
1	0	0

(A)

1	1	0
1	P	0
0	1	0

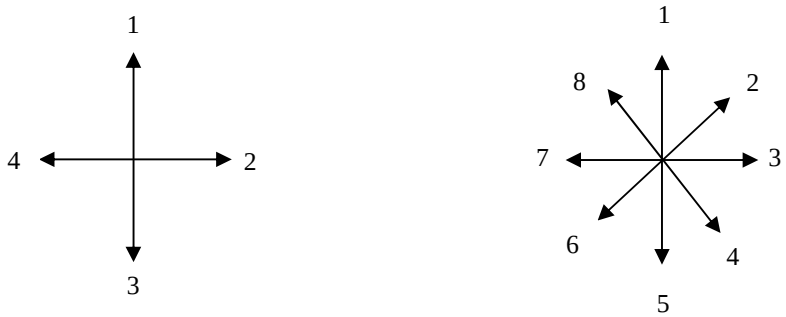
(B)

0	1	1
0	P	1
1	1	1

(C)

Figure (9): Examples of Contour Point.

Figure (10): Example for Signature Image after Contour Information Extraction.



(A): 4-Directional Chain Code. **(B): 8-Directional Chain Code.**

Figure (11): Neighbors of a Pixel and Value Assign to it
(A) (Left): Freeman Chain Code in Four Directions,
(B) (Right): Freeman Chain Code in Eight Directions.

Figure (12): (A) The Signature Image, (B) The Extracted Contours from the Signature.

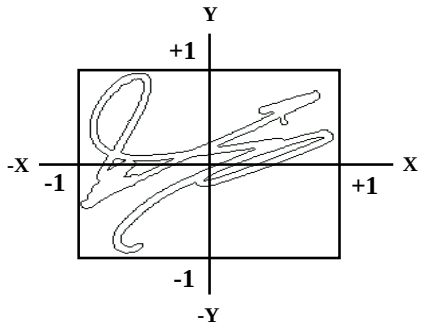


Figure (13): Central Coordinates Normalization

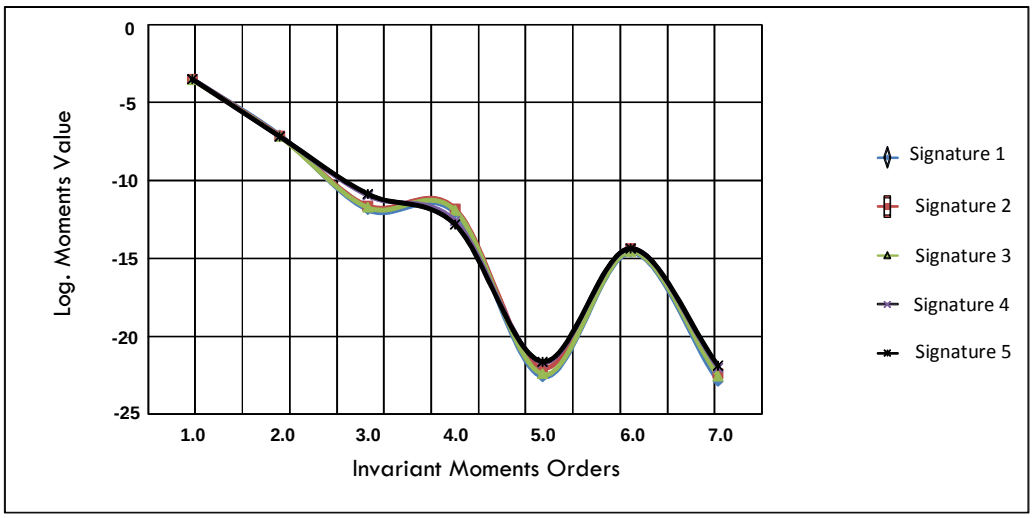


Figure (14): Illustrate the Relationship between Logarithm Moments Value and Invariant Moment Orders of Ahmed's Signature for Five Samples of the First

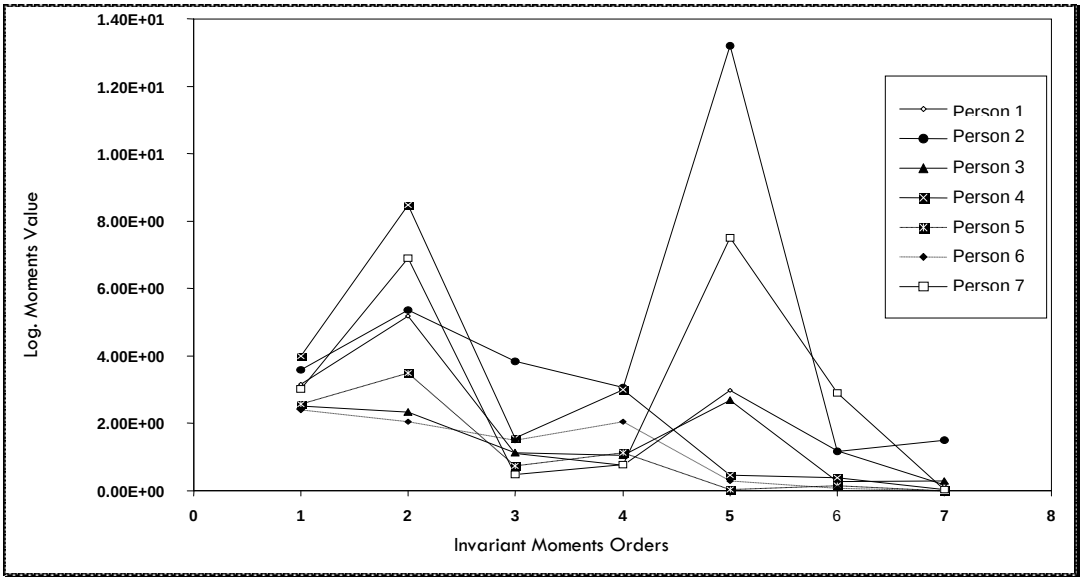


Figure (15): The Relationship between Logarithm Moments Value and Invariant Moment Orders of the First Contour for Different Signers.