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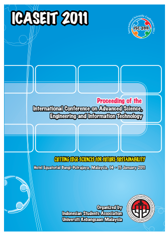

Off-line Arabic Character-Based Writer Identification – a Survey

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***Abstract*— Off-line writer identification requires transferring the text under consideration into an image file. This represents the only available solution to bring the printed materials to the electronic media. However, the transferring process causes the system to lose the temporal information of that text, which it can be gathered in on-line writer identification. Various techniques have been implemented to achieve high identification rates. These techniques have tackled different aspects of the identification system. Importance of writer identification system is to help mainly in forensic fields, historical document analysis and handwriting recognition system enhancement. Unfortunately, the Arabic writer identification system not achieves a satisfaction rate yet whereas certain process of features and classification still not recognized.**

***Keywords*— Arabic writer identification, Feature extraction, Classification, Off-line writer identification, Document Image Analysis.**

I. Introduction

Writer identification is considered as one of the hottest branches of pattern recognition has recently concerned by many researchers [1-7]since past decade till now due to its importance in forensics (section III-A) and critical criminals events appeared in the world, specially following of 9 September and the anthrax letters [4], is deeply involved in historical documents analysis [1, 4] , and handwriting recognition system enhancement as well [1]. The questioned handwritten text will be corresponding to the samples with known authorship which stored in available database, this process called Writer Identification.

Understanding Arabic script characteristics are compulsory for development of an Arabic writer identification system. A number of identification methods have been illustrated in section V.

Writer identification is classified into two categories, on-line and off-line [4]. In on-line case, the features gathered directly from signals that dispatched from digital devices. Further in off-line case the features gathered from the handwritten text which it acquired from scanned image [8]. It is considered as more complex than on-line case due to a lot of dynamic features of handwriting are missing, for instance pen-pressure, order of strokes, and writing quickness [4].

Moreover, writer identification can be text-dependant or text-independent (section III-D).

This survey is organized into six major sections, introduction, Arabic language characteristics, pattern recognition system, writer identification system, analysis of methods used in Arabic character-based writer identification systems and conclusions.

II. ARABIC LANGUAGE CHARACTERISTICS

Arabic language is spoken by more than 320 million peoples as native language; it has been used by more than one billion people in several life related activities especially in Islam religion [8]. Furthermore Arabic characters adapted by many other languages for instance, Persian, Kurdi, Jawi, and Urdu [8].

Arabic characters have many characteristics that make it difficult and much more challenging to be recognized. Firstly, they are cursive language which means that at the most Arabic written consists of connected characters to form a word. Secondly, Since it is cursive language the Arabic handwritings can take many shapes or ways to represent different words, one case for the handwriting is to combine two or more character vertically while writing a word which will cause ligature, such as the word "الخليفة" this word consists of four characters "ا ل خ ل ي ف ة" in this form of writing, the second character ل takes place on the top of the third character

خ so, instead of taking normal case for being two cursive characters like this case "لـخـ" they take a form of handwriting where the ligature does happen, as shown in Fig. 1.

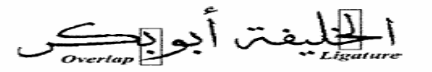

Fig.1 A sample of Arabic writing [8]

Thirdly, the overlapping is where characters have a place of crossover another character like in the word "ابوبكر", in this word "وبـ" are two Subwords crossed over. Fourthly, there are some small marks can be added to the Arabic characters based on grammatical bases to show the state of a word within a sentence, those additions called "Diacritics" which can change the meaning of the word according to its position, for instance the word 'كلية', which can be pronounced as either 'كُلِيّة' – 'college', or 'كِلْيَة'– 'kidney'. Finally, the structure for the Arabic characters will take different shapes depends on the position of the character within the word. At most we will have four shapes to represent the different cases for the character appearance in a word. Fig. 2 shows the different representation for the Arabic characters at any position within the word. In order each word may consist of one or more sub-words, where each sub-word may enclose more than one letter. As an example, consider the two word 'محمد –Mohammad' and 'خالد –Khalid'.

character	isloated	initial	middle	end
alif	أ	أ	ـا	ـا
ba'a	ب	بـ	ـبـ	ـب
ta'a	ت	تـ	ـتـ	ـت
tha'a	ث	ثـ	ـثـ	ـث
geem	ج	جـ	ـجـ	ـج
ha'a	ح	حـ	ـحـ	ـح
kha'a	خ	خـ	ـخـ	ـخ
dal	د	د	ـد	ـد
thal	ذ	ذ	ـذ	ـذ
ra'a	ر	ر	ـر	ـر
zyn	ز	ز	ـز	ـز
sin	س	سـ	ـسـ	ـس
shin	ش	شـ	ـشـ	ـش
sad	ص	صـ	ـصـ	ـص
dhad	ض	ضـ	ـضـ	ـض
ta'a	ط	طـ	ـطـ	ـط
dhah	ظ	ظـ	ـظـ	ـظ
ain	ع	عـ	ـعـ	ـع
ghin	غ	غـ	ـغـ	ـغ
fa'a	ف	فـ	ـفـ	ـف
qaf	ق	قـ	ـقـ	ـق
kaf	ك	كـ	ـكـ	ـك
lam	ل	لـ	ـلـ	ـل
meem	م	مـ	ـمـ	ـم
noon	ن	نـ	ـنـ	ـن
ha'a	ه	هـ	ـهـ	ـه
waw	و	و	ـو	ـو
ya'a	ي	يـ	ـيـ	ـي

Fig. 2 The Arabic alphabet set. Each character may have up to four different shapes.

III. PATTERN RECOGNITION SYSTEM

All variations of pattern recognition in handwriting systems include writer identification and verification, character recognition …etc have a common framework illustrate the nature of its work to accomplish its task as shown in Fig. 3.

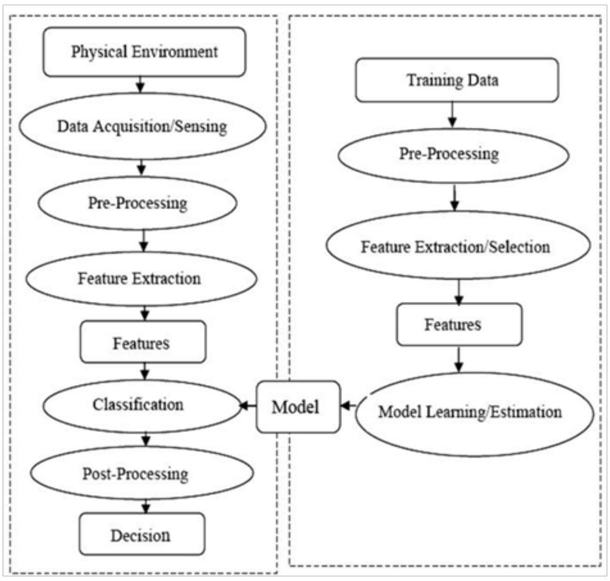

Fig. 3 Conventional Framework of Pattern Recognition System [9]

A. *Usage of Writer Identification within Forensics*

The significance of writer identification in forensics is determining the identity of the criminals in cases of threat letters for instance anthrax or ransom letters. There are many forensic systems in the field for instance, Fish and Script [4].

According to [4], there are three groups for text features that can be extracted from acquisitioned handwritten text image in forensic procedures:

- Fully automatic features computed from a region of interest (ROI) in the image;
- Interactively measured features by human experts using a dedicated graphical user-interface tool;
- Character-based features which are related to the allograph subset which is being generated by each writer.

B. *Handwriting Recognition vs. Writer Identification*

Writer identification is considered as one of the older handwriting recognition domain. In Table 1 we distinguish the difference between handwriting recognition and writer identification according to many aspects.

TABLE I
DIFFERENCES BETWEEN HANDWRITING RECOGNITION AND WRITER IDENTIFICATION

	Handwriting Recognition	**Writer Identification**
nature of its work and purpose	ability to represent the variety of differences in the handwriting style to achieve the correct interpretation of the text image. (generalization)	ability to determine the differences between the handwriting styles that are used to detect the correct writer's of the text image precisely. (writer discrimination)
concern by researchers	always interest by researchers [8]	extremely interest in the last decade[10-17]

According to [4] writer identification capable to minimize the ambiguities in pattern recognition process if writer's writing behaviour is available to the handwriting recognition system.

C. Writer Identification vs. Writer Verification

Writer identification and verification play a main rule in determining of the writer identity from handwritten images. The whole identification process enrolled into three main phases (assuming that required image pre-processing phase is done): feature extraction, feature matching and/or combination, and writer identification and verification.

In Table 2, we distinguish the difference between writer identification and writer verification according to concept and rule of success.

TABLE II
DIFFERENCES BETWEEN WRITER IDENTIFICATION AND VERIFICATION

	Writer Identification	**Writer Verification**
concept	most relevant writer's list will be returned after search in dataset of text images with known authorship.	a precisely result after comparing two text images which it will be exactly either they are belong to the same writer or not.
role of success	dataset will ranked based on variation gotten from the result of previous search process.	the factor distance between chosen sample will be hyperplane by compute the distance measurement then determining if the distance is less than threshold or not. if less, that mean the sample is written by same writer, otherwise written by others.

D. Text-Dependent vs. Text-Independent

All approaches of writer identification and verification can be categorized into two classes which are text-dependant and text-independent [3, 11]

In Table 3 we distinguish the difference between Text-independent and Text-dependent according to nature of its work and categories of used features.

TABLE III
DIFFERENCES BETWEEN TEXT-INDEPENDENT AND TEXT-DEPENDENT IN WRITER IDENTIFICATION AND VERIFICATION

	Text-Independent	**Text-Dependent**
nature of its work	text in the questioned document should not necessary be same as text in training process.	text in the questioned document should be same as text in training process.
categories of used features	structural approach extremely involved to extract features from the characters shape.	statistical and global writer identification techniques used widely to extract features from the text image.

E. Handwriting individuality

People gain the ability to improve their writing from the preliminary school and thought his life stages. There are many factors face the writer which they can affect his writing style individuality. For instance, in reality there are many factors can contribute in writer writing style as well as biological (genetic) and cultural (memetic).

IV. WRITER IDENTIFICATION SYSTEM

The writer identification system can be broken down into a number of stages: document acquisition, pre-processing, feature extraction and classification and the result of the identification process. Fig. 4 shows main common stages the Arabic writer identification system: Text image acquisition, pre-processing, feature extraction and classification.

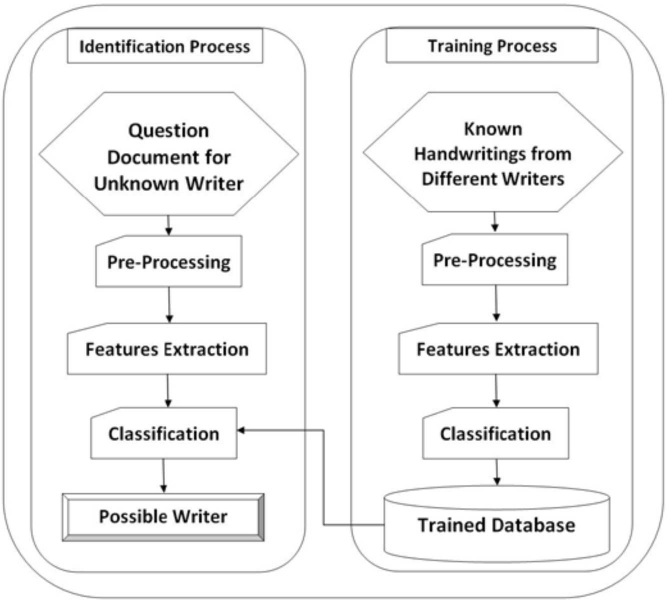

Fig. 4 General Writer Identification framework

A. Image Acquisition

The main function is to convert the text image from hardcopy into softcopy. Fig. 5 illustrates the deferent off-line text acquisition methods.

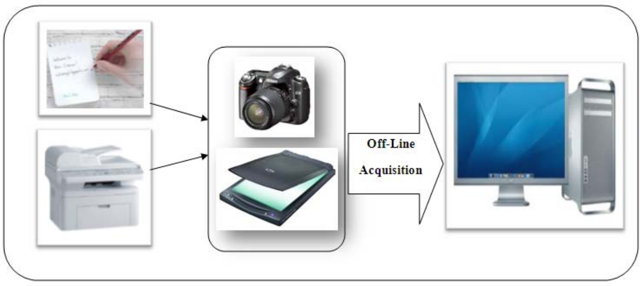

Fig. 5 Different text acquisition methods

Scanner is the most common device used to get the image comparing to other devices due to less noisy accrued during imaging process. The effectiveness of feature extraction phase is depending on document scanning quality. In the other hand the bad resolution will led to poor binarization and then poor readability when trying to extract the feature from text. When document copied several times strokes and black points will increase leading to ambiguity in extraction right features.

B. Pre-processing

Text image may have irregular in word spaces and line spaces alignment as well. Eliminating all these hindrances should be performed to enhance features extraction phase. Enhancement process may include many procedures, such as text lines localization, space normalization, text padding, thinning and skeletonization and smoothing. (e.g. Fig. 6).

C. Feature Extraction

1) *In General:* Feature extraction phase concern in how it can extract and represent the text image into set of features vectors to be used lately in classification phase. Extremely

features vectors can be extracting to get a high accuracy in classification these features vectors should be minimized by purification the set of non suitable features vectors, and then the rate of success identification can be improved. Feature extraction basically is how much the minimum features vectors can descript a large data precisely. A lot of variables used in the data analysis led to become complex problems. Powerful computation and large memory are indeed to carry out these huge numbers of variables. In addition, feature extraction deal with combine more than one variables to get satisfaction result.

2) *Types of Features in Image Processing*: Features types are divided depending on the criteria it will be deal with. Feature extraction used widely in optical character recognition systems, which it categorized as following [18]: *Low-level:* (Edge detection, Corner detection, Blob detection, Ridge detection, Scale-invariant feature transform), *Curvature*: (Edge direction, changing intensity, autocorrelation), *Image motion*: (Motion detection, Area-based, differential approach, Optical flow), *Shape Based*: (Thresholding, Blob extraction, Template matching, Hough transform [Lines, Circles/Ellipse, Arbitrary shapes]), and *Flexible methods*: (Deformable, parameterized shapes, Active contours).

3) *Software for Feature extraction:* Many commercial software and applications for feature extraction of image text are worth to mention such as the MathWorks Matlab, Scilab and NumPy[3, 11]

4) Feature Extraction in Writer Identification: Features fall under two main categorize

Fig. 6 Space and margin normalization (a) horizontal script (b) horizontal projection (c) line spacing normalization (d) vertical projection profile (e) word spacing normalization (f) text padding (g) The word "الكعبة" before Skeletonization (h) after Skeletonization Removal of grid lines (i) original image (j) restored image [8, 9]

- *Global Features (extracted from texture):* Manipulate the text image as image rather than handwriting. For instance, Gabor filters and co-occurrence matrices.
- *Local Features*: Manipulate the text image as handwriting; so many statistical properties of the text can be derived. For instance, average height, average width, average slope and average legibility of characters.

D. Classification

In pattern recognition classification means that evaluating the similarity among the objects that meet the desired features. In writer identification, classification means that labelling each handwritten into appropriate class.

Then classification techniques used to compute how many features are extracted from tested data are closed to those in stored data. The following are some examples of classification algorithms [2, 12, 17, 19]: Neural networks, Kernel estimation (k-nearest neighbour), Decision trees (Random forests), Bayesian networks, Hidden Markov models, Learning vector quantization, and Linear classifiers (Support Vector Machines, Perceptron).

V. ANALYSIS of METHODS are USED in ARABIC CHARACTERS-BASED WRITER IDENTIFICATION SYSTEMS- STATE of the ART

B. Helli et al. proposed four systems [5, 13, 20, 21] using PD100 data set for testing, which contains 500 samples from 100 writers and one system [20] using 350 samples written by 70 people .

In [5], two groups of feature extracted from data set using Gabor and XGabor tools in feature extraction phase. Then, generate a Feature Relation Graph (FRG) using the relations of the extracted features, this graph also called DAFRG (Directed Acyclic FRG). Later in classification phase a dynamic algorithm used to find the optimum similarity of two DAFRG. The average success of identification rate was 98%.

In [13], new classification methods proposed that measures the sequence similarity of sorted order of features, then the Longest Common Subsequence (LCS) method is used to compare sequence similarity. While the feature vectors were extracted using Gabor and XGabor filters. The average success of identification rate was 89%.

In [21], the same system as stated at [13] except the feature vectors where extracted using XGabor filters only. The average success of identification rate was 95%.

In [20], extended Gabor filter used to extract the percentage of the amount and style of the curves of writers writing style and extract the percentage of the amount and style of the writers' word lines. Then the Weighted Euclidian Distance (WED) used to select the first three distances which were in a same class. The average success of identification rate for text-dependent was 100% while for text-independent was 82%.

M. Abdi et al. [1, 10] proposed two different systems. In [1], system was tested using whole IFN/ENIT data set (26,459 samples by 82 writers), while in the [10] system was tested, partially, on the same data set (40 writers).

In [1], in feature extraction phase, feature vectors in form of Probability Distribution Functions (PDFs) and cross-correlation transformers of features used to captures individuality of writer by computing these feature vectors from Arabic word contour. The process of computing these feature vectors from is at the beginning obtaining the contours of Pieces of Arabic Word (PAW). Then, from the obtained contours the Minimum Perimeter Polygon (MPP) approximation is computed which used for extracting many measurements of edges such as length, directions, angle and curvature. Finally, counting and normalization of the measurements in PDFs and cross-correlation distribution is made.

For classification phase, a several common distance measurements are tested such as X^2, Euclidean / Standardized Euclidean, Manhattan …etc. The average success of identification rate was 90.2%. In [10], the same system as stated at [1] except it extract the same features from stroke after applying a thinning algorithm into handwriting images. The average success of identification rate was 92.5%.

F.Shahbi et al. proposed two systems [7, 16]. In [7], the system is text-independent approach while in [16], the system is text-dependent approach. In feature extraction phase, a new method is proposed using multi-channel Gabor filters, Gabor-energy and moments. Then the system implements these features with co-occurrence matrix and Said method.

In classification phase they use X^2 distance which is a simple and low computational cost classifier. The average successes of identification rate for both systems were 75%, 82.5% respectively.

S.S. Ram et al. proposed two systems [6, 15]. In [6], selection of first candidate by using grapheme feature performed. Then, restrict the domain of candidate by using area features and fuzzy approach. Finally, finalize the selection by using gradient features. In classification process, Euclidean distance & Fuzzy C-mean & K-Nearest Neighbours used in synchronization with the aforesaid three steps in feature extraction phase respectively. The average success of identification rate was 90% (250 documents, 50 writers).

While in[15], gradient features used to give information about strokes in short distances, then normalize histogram was computed by using previous features. In classification phase a feed forward multilayer Perceptron has been designed. The average success of identification rate was 94% (250 documents, 50 writers).

A. Rafiee et al. proposed a system [14]. In feature extraction phase five to seven feature vectors are available due to each text image in data base consist of five to seven lines. These features based on statistical characteristics of the handwriting for instance width of the character, lines, high of the text according to its base line. A horizontal histogram used to detect the base line then the raw with the maximum transitions between black and white is detected for extraction features process by: measure the length of each run of white pixels between two black runs, measure the median of values of inter-word spaces, and measure the ratio between the height of base line and the width of the writing.

In classification phase a feed forward Neural Network is applied. The average success of identification rate was 86.5% (20 documents, 130 lines).

K. Ubul et al. proposed system [17]. 2-D Gabor filter used in feature extraction phase generated 144 feature vectors. Generic algorithm technique successfully used to reduce the number of feature vectors. Supported Vector Machine (SVM), Weighted Euclidian Distance (WED) and KNN classifiers used in classification phase. The average success of identification rate was 88% (23 writers).

S. Al-Ma'adeed et al. proposed two systems [3, 11], in [3], which is text-dependent approach, edge-direction distribution for 4, 8, 12 and 16 angels, moment invariant methods and words measurement for instance height length, area, length from base line to the lower edge and length from base line to the upper edge are used as feature extraction methods. K-nearest neighbour classifier used in classification phase.

In [11] which the system text-independent approach, edge-hinge features and grapheme features were evaluated. K-nearest neighbour classifier used in classification phase. The average success of identification rate for text-dependent was 90% for Top-10 (3200 samples, 100 writers) while for text-independent was 90% (20 samples, 10 writers).

A. Al-Dmour et al. proposed a system [2]. Hybrid Spectral- Statistical Measures (SSMs) of texture was used in feature extraction phase, and then the most discriminant features were selected with a model for feature selection using hybrid support vector machine-Generic algorithm techniques. Linear Discriminant Classifier (LDC), Support Vector Machine (SVM), Weighted Euclidean Distance (WED) and K-Nearest Neighbours (K_NN) classifiers used in classification phase. The average success of identification rate was 90% (20 writers).

M. Bulacu et al. proposed a system [4]. In feature extraction phase 2 categories of features, textural features (Joint Directional Probability Distributions) and allographic features (Grapheme-Emission Distributions) were extracted. Combination of these features has been performed to achieve high performance of writer identification. K-mean, Kohonen Self-Organization Maps (SOM) clustering methods applied to a training set.

In classification phase, nearest-neighbour classification and X^2 distance is used for matching the individual features. The average success of identification rate was 88% (1750 documents, 350 writers of IFN/ENIT data set).

N. Feddaoui et al. proposed a system [9]. The pre-processing is done to the samples then banc of Gabor filters used to extract a signature vector representing the image text. Weighted Euclidean Distance (WED) classifier was used. The average success of identification rate was 96% (22 documents, 22 writers).

S. Gazzah et al. proposed three systems [12, 19, 22] using the same data set that consist of 180 samples from 60 writers for testing. In [12], combination of global (2-D discrete wavelet transforms for analysis the texture of text image) and Local features (Average Line height , space between sub-words, inclination of the ascenders and features extracted from dots) has been done in feature extraction phase. Modular Multilayer Perceptron (MMP) is used as classifier. The average success of identification rate was 95.68%.

In [22], same as [12] with adding extra global feature which is it Entropy. The average success of identification rate was 94.73%. While in [19], same of [22] with adding extra classifier which is it SVM. The average success of identification rate was 93.76%.

Some Summaries of these methods provided in Table IV.

TABLE IV

COMPARING OF SOME RECENT ARABIC WRITER IDENTIFICATION RESEARCHES

Authors [Ref.]	Features category	Features extraction method	Classifier	rate %	Text-Dependent / Independent
B. Helli et al. [5]	Global	Gabor & XGabor filters	Dynamic Algorithm	98	Text-Independent
A. Rafiee et al. [14]	Local	statistical characteristics features (width of the character, lines, high of the text according to its base line)	Feed forward Neural Network	86.5	Not Mentioned
S. Al-Ma'adeed et al. [3]	Local	Edge-Based Directional Probability Distribution Features	K-Nearest Neighbours	90	Text-Dependent
M. Bulacu et al. [4]	Global & Local	Joint Directional Probability Distributions & Grapheme-Emission Distributions	Nearest Neighbours & X2 distance	88	Text-Independent
N. Feddaoui et al. [9]	Global	Gabor filters	Weighted Euclidian Distance	96	Text-Independent
S. Gazzah et al. [12]	Global & Local	2-D Discreet wavelet transforms-lifting & Statistical features	Modular Multilayer Perceptron	95.68	Not Mentioned

VI. CONCLUSIONS

The Writer Identification System is the process of recognizing the identity of question text image author, by matching the classified features of questioned text with known authorship text image. Many factors influenced this system performance through variability in handwriting such as generic and cultural which they determine the habitual the writing process of people.

The significance of writer identification system is to help mainly in forensic fields, historical document analysis. Unfortunately there are no intensive searches onto Arabic handwriting identification. In addition this survey can assist the interested researcher to get a comprehensive view and where is it trend on.

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