An Empirical Evaluation of Off-line Arabic Handwriting And Printed Characters Recognition System

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ABSTRACT

Handwriting recognition is a challenging task for many real-world applications such as document authentication, form processing, historical documents. This paper focuses on the comparative study on off-line handwriting recognition system and Printed Characters by taking Arabic handwriting. The off-line Handwriting Recognition methods for Arabic words which being often used among then across the Middle East and North Africa people. In this paper we are proposing off-line Arabic handwriting and printed characters and the language used by the majority of the Middle East. We are using discrete Hidden Markov Models (HMM) for Arabic handwriting and printed characters for the final recognition. In this paper after preprocessing step the characters are auto-segmented using a recursive algorithm as sequences of connected neighbors along lines and curves and Arabic words are first pre-classified into one of known character groups, based on the structural properties of the text line. The proposed system was trained and tested Arabic character images. The Arabic characters were written by the different people on a preformatted paper and the method recognizes the Arabic handwriting in print style format. A comparative Experimental result has shown 93.40% recognition rate for the Arabic handwriting and 97.30% recognition rate for the Arabic printed characters.

Keywords: *Recognition, Hidden Markov Models (HMMs), Arabic Word, Feature Extraction, off-line handwriting.*

1. Introduction

Although the problem of handwriting recognition has been considered for more than 60 years there are still many open issues, especially in the task of unconstrained handwritten sentence recognition [1]. The human eye can see and read what is written/displayed either in natural handwriting or in printed format. The same work in case the machine does is called handwriting recognition, which is the common definition. Handwriting recognition has been a popular area of research for a few decades under the purview of pattern recognition and image processing [2]. The domain of handwriting recognition can be divided into on-line and off-line recognition. To strengthen the performance of handwriting recognition has been a major goal in this field. Besides the basic handwriting recognition algorithms, various post processing methods are proposed to improve the accuracy of recognition. The techniques for on-line and offline recognition may be quite different, but the post processing methods are possibly similar for both of them [3]. Off-line character recognition takes a raster image from a scanner (scanned images of the paper documents), digital camera or other digital input sources. The image is binarized through threshold technique based on the color pattern (color or gray scale), so that the image pixels are either 1 or 0. The recognition of cursive handwriting is still an open problem due to the existence of many difficulties such as the variability of the handwritten styles and shapes, writing skew or slant and the size of the lexicon. Unconstrained Arabic handwriting is naturally cursive and challenging for off-line recognition systems. The letter shapes are context sensitive, inter and intra word spaces and character ligatures are of variable lengths, words include many dots and diacritical marks which change word meaning and indicate vowels. The writing is set on a baseline where character connections occur, and from where descending and ascending characters extend [4]. Arabic printed and handwriting recognition has widely used HMM-based systems because of the connected nature of the Arabic script.

2. Arabic Written Characteristics

The Arabic script evolved from the Nabataean Aramaic script. It has been used since the 4th century AD, but the earliest document, an inscription in Arabic, Syriac and Greek dates from 512 AD [5]. The Aramaic language has fewer consonants than Arabic, so during the 7th century new Arabic letters were created by adding dots to existing letters in order to avoid ambiguities. The Arabic one of the six official languages of the United Nations, Arabic is a Semitic language spoken by between 300 and 400 million native speakers, and a further 250 million non-native speakers, in nearly twenty countries in the Middle East and North Africa [6]. Arabic is quite a challenging language to learn for a number of reasons: it uses a number of sounds pronounced way back in the throat that can be tricky for speakers of English and other languages [7]. It is written with a cursive alphabet running from right to left in which the letters change shape depending on their position in a word [8]. An Arabic word character may be partitioned into three zones: upper zone, middle zone and lower zone. The

Arabic characters is more difficult than others, such as Latin , Chinese and Hindi [9].

Table 1 - Position-dependent shapes are shown for each letter of Arabic characters

No	Character Name		Isolated	Connected		
				Beginning	*Middle*	*End*
1	Alif	ألف	ا	ا	ـا	ـا
2	Baa	باء	ب	بـ	ـبـ	ـب
3	Taa	تاء	ت	تـ	ـتـ	ـت
4	Thaa	ثاء	ث	ثـ	ـثـ	ـث
5	Jeem	جيم	ج	جـ	ـجـ	ـج
6	Haa	حاء	ح	حـ	ـحـ	ـح
7	Khaa	خاء	خ	خـ	ـخـ	ـخ
8	Daal	دال	د	د	ـد	ـد
9	Thaal	ذال	ذ	ذ	ـذ	ـذ
10	Raa	راي	ر	ر	ـر	ـر
11	Zaay	زاي	ز	ز	ـز	ـز
12	Seen	سين	س	سـ	ـسـ	ـس
13	Sheen	شين	ش	شـ	ـشـ	ـش
14	Saad	صاد	ص	صـ	ـصـ	ـص
15	Dhaad	ضاد	ض	ضـ	ـضـ	ـض
16	Ttaa	طاء	ط	طـ	ـطـ	ـط
17	Dthaa	ظاء	ظ	ظـ	ـظـ	ـظ
18	Ain	عين	ع	عـ	ـعـ	ـع
19	Ghen	غين	غ	غـ	ـغـ	ـغ
20	Faa	فاء	ف	فـ	ـفـ	ـف
21	Qaf	قاف	ق	قـ	ـقـ	ـق
22	Kaf	كاف	ك	كـ	ـكـ	ـك
23	Lam	لام	ل	لـ	ـلـ	ـل
24	Mem	ميم	م	مـ	ـمـ	ـم
25	Noon	نون	ن	نـ	ـنـ	ـن
26	Haa	هاء	ه	هـ	ـهـ	ـه
27	Wow	واو	و	و	ـو	ـو
28	Yaa	ياء	ي	يـ	ـيـ	ـي

The Arabic alphabet contains 28 letters. Each has between two and four shapes and the choice of which shape to use depends on the position of the letter within its word or subword. The shapes correspond to the four positions: beginning of a (sub)word, middle of a (sub)word, end of a (sub)word, and in isolation. Table 1 shows each shape for each letter. Letters without initial or medial shapes shown cannot be connected to the following letter, so their "initial" shapes are simply their isolated shapes and their "medial" shapes are their final shapes.

3. Related Work

The Offline Arabic Handwriting and printed characters recognition present several research challenges in the area of document analysis and recognition. In 1987, Almuallim and Yamaguchi proposed one of the first methods for Arabic handwriting recognition [10]. It used the skeleton representation and structural features for word recognition. Words were segmented into "strokes" which were classified and combined into characters according to the features. The recognizer was the set of classification rules. Goraine et al. presented a structural approach in 1992 [11]. It operated on whole words and was applied to typewritten and handwritten words. After segmentation points were estimated from skeletons, structural features and a rule-based recognizer identified each letter. A dictionary was used to confirm or correct the results. In 1992, Al-Yousefi and Udpa introduced a statistical approach for the recognition of isolated Arabic characters [12]. It included the segmentation of each character into primary and secondary parts (such as dots and small markings) and normalization by moments of vertical and horizontal projections. The features were nine measurements of kurtosis, skew, and relationships of moments, and the recognizer was a quadratic Bayesian classifier. Related work by Clocksin and Fernando in 2003 addressed the domain of Syriac manuscripts [13]. Also, a West Semitic language, Syriac is less grammatically complex than Arabic and was a primary language for theology, science, and literature from the third century AD to the seventh century AD. The system used full image representation of individual characters and sets of features based on moments. In 2005, Mozaffari et al. Proposed a method for the recognition of Arabic numeric characters which is structural and also uses statistical features [14]. Endpoints and intersection points were detected on a skeleton then used to partition it into primitives. Eight statistical features were computed on each primitive, the features for all primitives were concatenated, and the result was normalized for length. Also, In 2005, El-Hajj et al. Demonstrated the benefit of features based on upper and lower baselines, within the context of frame-based features with an HMM recognizer [15].

In this study, we exploit the use of Hidden Markov Models (HMMs) for off-line Arabic handwriting and printed characters recognition. HMMs have been widely used in the field of speech recognition and more recently in handwriting recognition. Although most of these handwriting recognition applications concentrate on cursive handwriting and on-line handwriting, there have been attempts where HMMs were used on isolated handwritten characters [16]. The Miled and Ben Amara combined the algorithm of [17] with a planar hidden Markov model (PHMM) to recognize machine printed and handwritten words in 2001 [18]. They chose the planar model to handle the planar nature of writing and the specific situation in which one letter is directly above another. In 2001, Dehghan et al. Presented an HMM-based system whose features were histograms of Freeman chain code directions in regions of vertical frames [19]. No segmentation was used. There was one discrete HMM for each city class. Khorsheed applied an HMM recognizer with image skeletonization to the recognition of text in an ancient manuscript (2003) [20]. No segmentation was done. One HMM was constructed from 32 individual character HMMs, each with an unrestricted jump margin. Structural features were used and the recognition rate was 87 percent (72 percent) with (without) spell-check. A2003 approach by Pechwitz andMa¨rgner used 160 semi continuous HMMs representing the characters or shapes [21]. It thinned each word and used columns of pixels in the blurred thinned image as features Safabakhsh and Adibi applied a continuous-density variable-duration hidden Markov model [22] to the recognition of handwritten Persian words in the Nastaaligh style (2005) [23]. This style contains many vertically overlapping letters and sloped letter sequences, which present problems for the ordering of characters and for baseline detection. Their system removed ascenders and descenders before the primary recognition stage to avoid incorrect orderings and was baseline-independent. The paper focuses on recognition at the segmented character's level and therefore assumes pre-segmentation of Arabic characters. The recognition process is unknown split into two main sections: pre-classification and recognition using Hidden Markov Models.

4. General Framework of Recognition System

This section describes all the modules used in the recognition system. Figure 1 shows the offline Arabic recognition general framework. Transforming the written text in papers or transcript to digital format is a necessary step in the offline Arabic handwriting recognition.

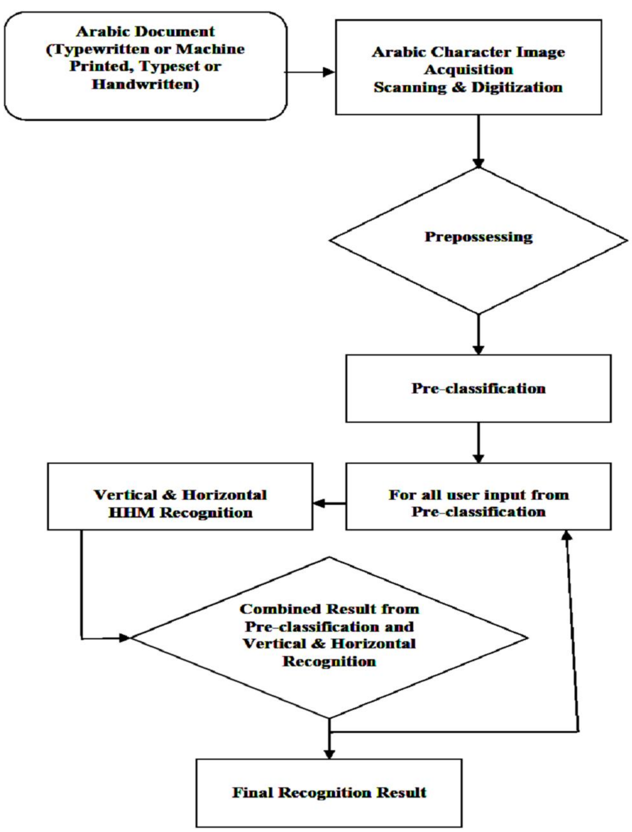

Fig. 1 General Framework of Recognition System

In the image acquisition the paper is scanned or captured. The scanning speed, document types and scanning quality need to be considered in the document scanning. Preprocessing is necessary to perform several document analysis operations prior to recognizing text in scanned documents. This component is needed to remove insignificant scanning artifacts and noise. The preprocessing stage is also necessary to increase the uniformity in texts which is quite essential for recognition system. It is also used to reduce the redundancy present in the data. Although on-line and off-line data are digitized at different resolutions and with different devices, the noise problem is the same, data points are discrete and may deviate from optimal results. With off-line data, this error is caused by the discrete nature of the image itself and the thresholding operation.

The offline Arabic handwriting recognition systems usually accept inputs in bi-level format or to be more specific binary format. Generally, the input text images in grayscale. Hence, we need a preprocessing stage called Binarization. It converts from grayscale image to bi-level image taking into consideration a threshold pixel value for comparison. The threshold pixel value can be computed based on the histogram of the gray values of the images. Figure 2 shows the Arabic handwritten word image Rayal ريال after converting from grayscale to binary format using a global threshold.

(a) (b)

Fig. 2 The example of binarization Arabic handwritten word image Rayal ريال In Grayscale format (a) and In Binary format (b)

The Segmentation problem is the most difficult and important issue in the offline Arabic handwriting recognition. It directly affects the feature extraction and classification process. The Arabic text segmentation methods can be classified broadly into two approaches: First is called holistic approach or segmentation-free approach. This technique aims to segment the Arabic text to words or sub words [24]. Image segmentation is one of the primary steps in image analysis for object identification. The main aim is to recognize homogeneous regions within an image as distinct and belonging to different objects. Segmentation stage does not worry about the identity of the objects. They can be labelled later. The segmentation process can be based on finding the maximum homogeneity in grey levels within the regions identified. The feature extraction process is also an important stage in the offline Arabic handwriting recognition system. It has a big influence on the classification stage. The feature extraction process is used to analyze the segmented features of the Arabic text for the classification purposes, and in some cases the combination between several segmented features could enhance the overall recognition rate [25]. An important stage in every recognition problem is feature extraction, when the characters are handwritten, where the features are varied substantially. Its purpose is to reduce the data by measuring certain features or properties that can distinguish different classes of input patterns [26]. After preprocessing, some features are extracted from the unknown character which is then classified in the class whose members have the most similar features. This process is called recognition process. The issues in this process are finding both descriptive and discriminating features, selecting a way to compare them, creating the classification rules. These issues are highly dependent on each other.

5. The Recognition Methodologies Hidden Markov models (HMMs)

The Hidden Markov Models (HMMs) have been successfully applied to handwritten recognition systems. They offer several advantages, mainly the automatic training on non-segmented words and combined segmentation recognition. Hidden Markov models (HMMs) are also appropriate for learning characteristics that are difficult to describe intuitively [27]. Conventional HMMs model one-dimensional sequences of data and contain states and probabilities for transitioning between them according to an observed sequence of data or observations [28]. Assume that, at each time step, the system was in one of N possible states and produced one of M possible observation symbols, the choice depending on the probabilities associated with that state figure 3 shows.

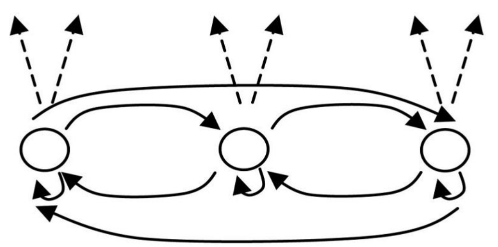

Fig. 3 The HMM with three states and two possible observation symbols at each.

The goal is to reconstruct the state sequence ("path") from the observations to learn the meaning of the data. For text recognition, the observations could be sets of pixel values and states could represent parts of letters. An alternative to finding a path in a single model is accepting the most probable of several models [29]. The Pre-segmentation free approach is important especially in case of cursive handwritten, e.g. Arabic handwritten where the characters are often connected. The recognition approaches can be either "holistic" or segmentation-based. "Holistic" means that words are processed as a whole without segmentation into characters or strokes [30]. In segmentation-based approaches, whole or partial characters are recognized individually after they have been extracted from the text image. In this paper we propose Hidden Markov Models are used to find the probability of Arabic characters and words.

N, the number of states in the model. The set of states in the model is $X = \{1,2, \ldots , N\}$, the state at time t is denoted as q_t

Y, the discrete alphabet size. We denote the individual symbols as $V = \{v1, v2, \ldots , v_M\}$.

A $= \{ a_{ij}\}$, the state transition probability distribution where

$$a_{ij}=P[q_{t+1} = x_j / q_t = x_i], 1\leq i , j\leq N$$

B $= \{b_j (k)\}$ the observation symbol probability distribution in state j, where

$$b_j (k) = p[v_k \text{ at } t \mid q_1 = x_j], 1\leq j \leq N , 1\leq k \leq N$$

$\Pi = \{ \pi_i\}$, an initial state distribution where

$$\pi = p [q1=x] , 1\leq l \leq N$$

A compact notation for the above HMM would be

$$\lambda = \{A,B,\pi\}$$

The Baum-Welch algorithm, with multiple observation sequences .Then, for a given observation sequence $S = \{s_1, s_2,\ldots s_T\}$, the HMM is used to compute $p [s \mid \lambda]$ where T is the length of the sequence. Two HMMs are created for every character, one for modeling the horizontal information and the other for modeling the vertical information. The discrete hidden Markov character models are trained using standard procedures. The numbers of states for all the character HMMs is fixed and no skip states are allowed. Only the pre-classified pretendent characters are passed on for HMM recognition. Two log probabilities for each pretendent character are calculated using the horizontal direction HMM and vertical direction.

6. Proposed Approach

In this paper we are using normal sized paper typically include Arabic handwriting and printed characters to collect sample character images. This normal paper is scanned and binarized using an adaptive threshold technique. After that this image is segmented into constituent text line using the horizontal projection profile. Figure 4 shows the reference line extraction using horizontal projection profiles. The task of detecting this main body is known as zone or baseline determination. In the reference line finding algorithm, a text line is divided into four lines as the lower line, lower baseline, upper baseline, and upper line, which define three zones: upper zone, middle zone and lower zone. The method is based on an analysis of the horizontal density histogram. A word and its histogram of horizontal densities, called the horizontal projection profile. A simple procedure now is to look for peaks of the first derivative of the density function and claim the lower and upper baselines at the maximum and minimum, respectively. The zero values in the projection profile correspond to horizontal gaps between lines. The maximum and minimum zero value positions adjoining a text line are taken as the line boundaries corresponding to

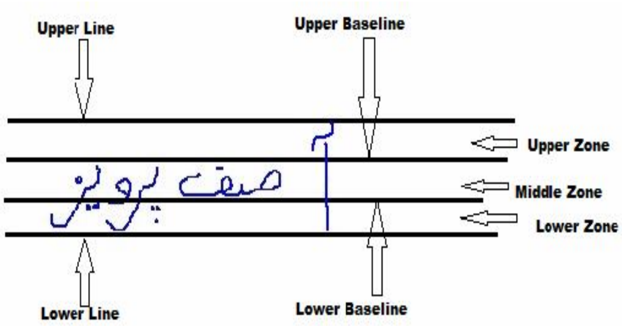

Fig. 4 The reference line extraction using horizontal projection profile

The lower line and upper line respectively. The upper baseline and lower baseline are identified by the first derivative of the horizontal projection profile. After the reference lines have been found, the individual words and characters are extracted using the vertical projected profile of each text line. Then the characters are segmented using the recursive algorithm. This algorithm is illustrated in below.

Set y_{ij} 0 Y ($0 \leq i \leq 255$ & $0 \leq j \leq 255$)
// Pixels set neighbor
N_{ij} ($y_{i-1,j-1}$, $y_{i,j-1}$, y_{i+1j-1},
$y_{i-1,j}$, y_{ij}, $y_{i+1,j}$,
y_{i-1,j_1}, $y_{i,j+1}$, $y_{i+1,j+1}$)
//Segmentation boundary for word
If (y_i<l) then l = y_i;
If (y_j<t) then t = y_j;
If (y_i>r) then r = y_i;
If (y_j>b) then b = y_j;
for segmentation
begin
for (int i = 1 to N)
begin
for (int j = 1 to N)
begin
If y_{ij} == 0 then N_{ij} = black;
end
end
end

When objects are described by their skeletons or contours, they can be represented more efficiently than simply by OFF and ON valued pixels in a raster image. One common way to do this is by chain coding, where the ON pixels are represented as sequences of connected neighbors along lines and curves. Instead of storing the absolute location of each ON pixel, the direction from its previously coded neighbor is stored. A neighbor is any of the adjacent pixels in the 3x3 pixel neighborhood around that center pixel.

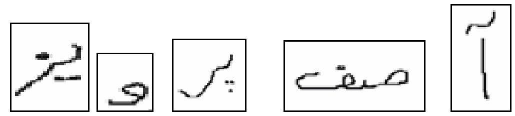

Fig. 5 The Auto-segmented images of Arabic handwriting

Once the characters are segmented, the minimum bounding box of each character is identified deleting the white space around it. Upper and lower boundary values of the minimum bounding box relative to the character lines are sent to the next stage for preliminary classification. Figure 5 shows the scanning images and Auto-segmented images of Arabic handwriting. In this paper we are selection of feature extraction methods is probably the single most important factor in achieving high recognition performance. The recognition of character accuracy rate depends on what features are being used. In selecting a feature, certain criteria must be employed. In our feature extraction design there include two modules. The defining zone is the first module of the proposed of novel feature extraction method which defines the zone for the normalized data image. Basically, the input normalized image 24×24 is partitioned into 2×2 zones, each comprising 12×12 elements. Secondly, defining zone data region module distinguishes the zone data region so that different representations of the same features can be properly identified. Each image is divided into vertical and horizontal strip. Each strip is then subdivided into sections of size 3x3 pixels. A vector is created in each of the two directions using the pixel density of each section.

7. Experimental Results

The experimental results have proven to show excellent recognition rate for both Arabic handwriting and printed characters. In our experiments, the training set contained 1000 characters from each character class. The test set contains about 200 characters. All the data were obtained from five writers on the formatted papers. Each document contained 22 text lines of some meaningful words with approximately Arabic handwriting and printed character and words. Writers were allowed to write freely with a varying frequency of characters of each class. A total of 60 text lines was subjected to segmentation and reference line identification. The segmentation procedure was able to correctly identify all the reference lines. The preliminary classification resulted in 99.8% accuracy for handwritten characters and 100% accuracy for Arabic printed characters. The pre-classified images were then fed into HMM recognition system. The results of the HMM recognition rate are as follows.

Arabic Printed Characters	**97.30%**
Arabic Handwritten Characters	**93.40%**

8. Conclusion

Finally, the word recognition has been one of the active and challenging research areas in the field of image processing and pattern recognition. In this paper, the Arabic language characteristics were clarified, and the operations of Arabic offline character recognition system stages were discussed and clarified. We are primarily introduced technology of discrete hidden Markov models based on offline information. Arabic character recognition is more difficult than the other languages such as Latin or Chinese and Hindi because the text is written cursively in addition to the complexity of the text characteristics. In this paper we have presented a system for recognizing Arabic handwriting and printed characters. A discrete hidden Markov model based classifier as used for the recognition. Our feature extraction method reduced the two dimensional spatial information of character images into a single dimension array of values, thereby throwing away some information. The typical Arabic handwriting and printed characters system consist of five components: image acquisition, preprocessing, segmentation, feature extraction and classification (recognition). Each of these contributes to the final recognition rate to improve of the Arabic handwriting and printed characters. Each stage has an impact on the effectiveness and efficiency of the system.

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