Large Vocabulary Arabic Online Handwriting Recognition System

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ABSTRACT

Arabic handwriting is a consonantal and cursive writing. The position of the character and its context define its shape. The analysis of Arabic script is further complicated due to obligatory dots/strokes that are placed above or below most letters and usually written delayed in order. Due to ambiguities and diversities of the different writing styles, recognition systems are generally based on a set of possible words called lexicon (vocabulary). When the lexicon is small, recognition accuracy is more important as the recognition time is minimal. On the other hand, recognition speed as well as the accuracy are both critical issues when handling large lexicons. Arabic language is rich in morphology and syntax which makes its lexicon large. Therefore, a practical online handwriting recognition system should be able to handle the large lexicon of the Arabic language with reasonable performance in terms of both accuracy and time.

In this paper, we introduce a fully-fledged Hidden Markov Model (HMM) based system for Arabic online handwriting recognition that provides solutions for most of the difficulties inherent in recognizing the Arabic script. A new preprocessing technique for handling the delayed strokes is introduced. We use advanced modeling techniques for building our recognition system from the training data to provide more detailed representation for the differences between the writing units, minimize the variances between writers in the training data, enhance the models discrimination power and have a better representation for the features space. The system results are enhanced using an additional post-processing step to rescore multiple hypothesis of the system result with higher order language model and cross-word HMM models. The system performance is evaluated using two different databases covering small and large lexicons. Our proposed system outperforms the state-of-art systems for the small lexicon database. Furthermore, it shows promising results (accuracy and time) when supporting large vocabulary with the possibility for adapting the models for specific writers to get even better results.

1. Introduction

The wide spread use of pen-based hand held devices such as PDAs, smartphones, and tablet-PC, increases the demand for high performance on-line handwritten recognition systems. This man machine interface method is an alternative for the traditional keyboard with the advantages of being more easy, friendly, and natural.

Automatic Handwritten Recognition can be classified into two types: on-line and off-line recognition. Off-line recognition does not require a direct interaction with the user. It just applies feature extraction on the scanned images of the handwritten text. In on-line recognition, a time ordered sequence of coordinates (representing the movement of the pen) is captured and fed to the system as a sequence of 2D-points in real-time, thus tracking additional temporal data not present in off-line recognition. Online handwriting recognition is becoming more and more important in the modern world due to the spread of hand-held devices. It becomes more challenging when dealing with cursive language like Arabic.

Arabic text, both handwritten and printed, is cursive. The letters are joined together along a writing line. In contrast to Latin text, Arabic is written right to left, rather than left to right. It contains dots and other small marks that can change the meaning of a word. The shapes of the letters differ depending on whereabouts in the word they are found. The same letter at the beginning and end of a word can have a completely different appearance. Along with the dots and other marks representing
vowels, this makes the effective size of the alphabet about 160 characters.

The morphology of the Arabic language poses special challenges to computational natural language processing systems. The Arabic language has large lexicons containing 30,000 to 90,000 words (Wshah et al. 2010). Research in on-line handwritten word recognition has traditionally concentrated on relatively small lexicons. Several Researchers (Abdelazeem and Eraqi (2011); Eraqi and Azeem (2011); Ahmed and Azeem (2011); Hosny et al. (2011)) proposed online handwriting recognition systems for the Arabic language. However, their approaches are developed for small vocabulary (1000 words) and they did not aim at solving the challenges imposed by supporting large vocabulary lexicons. On the other hand, Biadsy et al. (2006) proposed a HMM-based handwriting recognition system with support for a 40,000 words lexicon. However, their method for handling the delayed strokes requires the initial detection of the delayed strokes which is a challenging task by itself. Furthermore, it is sensitive to the writing styles and could misplace the projection of the delayed strokes in the word body. Finally, they tested their method on a very small dataset consisting of around 3,000 words collected from 10 writers. Considering the rich morphology and syntax of the Arabic language makes it a must for an effective recognition system to handle large vocabulary lexicon.

In this paper, we introduce a large vocabulary HMM-based system for online Arabic handwriting recognition. This system supports a vocabulary size of 64k unique words which represents 92% coverage for the Arabic language. Our system is inspired with the similarity between speech recognition and handwriting recognition, as both of them can be considered a stochastic process with sequential nature. Several advanced HMM modeling and training techniques that are adopted in most state of the art speech recognition systems are used for building our system models. A novel preprocessing method for handling delayed strokes is presented. Unlike previous efforts, it solves the delayed strokes problem in most of the writing styles.

Our Contributions: In summary, our specific contributions are:

1. A fully-fledged Arabic Online Handwriting system with a support for a large vocabulary (64,000 unique words).
2. A novel preprocessing method for handling delayed strokes is presented. Unlike previous efforts, it solves the delayed strokes problem in most of the writing styles.
3. With only few data samples, our models can be adapted for certain writers and have significantly better performance.
4. Our system outperforms state-of-the-art approaches for small vocabulary. Furthermore, it shows very promising results in terms of both accuracy and time when supporting a large vocabulary.

System Overview: Figure 1 shows the system block diagram. Preprocessing operations are used to reduce the effect of the handwriting device noise and the handwriting irregularity. Then the delayed strokes are rearranged to match the structure of the HMM model. A new approach for delayed strokes handling is developed. Our approach overcomes the limitations of the method introduced by Biadsy et al. (2006). Our method does a finer projection to avoid the misplacing of the projection points into wrong places in the written word body. An advantage of our approach is that, it does not require the initial detection of the delayed strokes as all the strokes of the input are handled similarly. Several features are extracted from the handwriting signal and are used to train the HMM models. In the recognition phase, our trained models are used with the application dictionary by a decoding engine to select the best words that match the user input. Optionally, the output of the first recognition phase can be passed to another post-processing step to rescore multiple hypothesis of the system results with a higher order language model.

Paper Organization: The paper is organized as follows: In Section 2 we describe the related work. Section 3 describes the pre-processing, feature extraction and the delayed strokes rearrangement steps. Section 4 describes the HMM models structure and training procedure in addition to the post-processing phase. The system evaluation using small and large databases is introduced in Section 5. Section 6 includes the final conclusions and a plan for the future work.

2. Related Work

Early research on online Arabic handwriting recognition focused on the recognition of isolated characters. El-Wakil and Shoukry (1989) proposed a method for the recognition of handwritten Arabic characters drawn on a graphic tablet using writer independent features and Freeman-like chain code. Kharma and Ward (2001) proposed the use of a mapping for the handwritten characters to normalize the orientation, position, and size of the input pattern. Mezghani et al. (2002) investigated a method based on Kohonen maps and their corresponding confusion matrices which serve to prune the error-causing nodes, and to combine them consequently. Al-Taani (2005) proposed an efficient structural approach for recognizing on-line Arabic handwritten digits based on the changing signs of the slope values to identify and extract the primitives.

To recognize larger units, Almuallim and Yamaguchi (1987) proposed a structural recognition method for cursive Arabic handwritten words by segmenting them into strokes. These strokes are classified using their geometrical and topological properties then they are combined into a string of characters that represents the recognized word. Alimi (1997) developed an online writer dependent system to recognize Arabic cursive words based on neuro-fuzzy approach. Elanwar et al. (2007) proposed a system to recognize online Arabic cursive handwriting based on rule-based method to perform segmentation and recognition of word portions in an unconstrained cursive handwritten document using dynamic programming. Daifallah et al. (2009) developed an on-line Arabic handwritten recognition system based on an arbitrary stroke segmentation algorithm followed by segmentation enhancement, consecutive joint connections and segmentation point locating.

The structural-based approaches are based upon the idea that character shape can be described in an abstract fashion without
paying too much attention to the shape variations that necessarily occur during the execution of that plan. These approaches try to segment the input pattern before applying recognition for the produced segments. Consequently any error in the segmentation phase is unrecoverable and would affect the accuracy of the final recognition result. A better alternative was proposed by using HMM models which are doubly stochastic models that proved to achieve good performance for sequences recognition. Using HMM models the pattern segmentation and recognition can be achieved simultaneously using an integrated search technique such as Viterbi or A-star.

Khorsheed (2003) have successfully used HMM models for the recognition of off-line handwritten Arabic script. In their approach, word level HMM is composed of smaller interconnected models that represent the character level models. Each character model is a right-to-left HMM. Structural features are extracted from overlapping vertical windows that scans the input pattern sequentially from right to left with same direction as the model structure.

Recently, several efforts (Abdelazeem and Eraqi (2011); Eraqi and Azeem (2011); Ahmed and Azeem (2011); Hosny et al. (2011)) proposed HMM-based online handwriting recognition systems. However, their approaches are developed for small vocabulary (1000 words) and they did not aim at solving the challenges imposed when supporting large vocabulary lexicons.

Handling Delayed Strokes When dealing with on-line handwriting, the right-to-left order of writing is not guaranteed. Usually writers tend to use some delayed strokes by moving backward to add some diacritics. In Arabic, there are 17 characters out of 28 are written with delayed strokes. So the percentage of characters with delayed strokes is 60% and will be higher if we included the different diacritics. The delayed strokes make disturbance in the order of the writing sequences. It results in a mismatch with the expected order of the input sequence for the HMM model according to the constraint of the right-to-left model structure. To deal with this challenge, four different solutions were proposed in the literature.

Figure 2 includes a color legend that is used to show the writing order of different strokes in a word. The colors describe the order on which the different strokes are written. For example, this sample has four strokes, the first one is written in yellow while the second one is written in white green and so on.

In the first approach by Abdelazeem and Eraqi (2011), the delayed strokes are totally discarded from the handwriting in the preprocessing phase. This method could not be employed effectively since the information that makes letters different from others is the number and position where the dots are located. Eliminating delayed strokes will cause a tremendous ambiguity, particularly when the letter body is not written clearly. Furthermore, some Arabic letters have a similar shape of composition with some letters, such as: the letter(s) ﯽس (b + t + y) (Without dots).

The second approach is introduced by Ha et al. (1993). Delayed strokes are detected in the preprocessing phase and then used in a post-processing phase to differentiate between ambiguous words. The detection of the delayed strokes is by itself a challenging task and the errors in this preprocessing step can result in discarding segments form the main body of the handwritten words. For example, in Figure 3 there are no delayed strokes. However, letters are totally overlapped with each other, hence, they can be detected as delayed strokes.

The third approach is introduced by Starner et al. (1994); Hu et al. (2000); it keeps the delayed strokes with special manipulation. In Starner et al. (1994)’s approach, the end of a word is connected to the delayed strokes with a special connecting stroke. The special stroke indicates that the pen was raised and results in a continuous stroke sequence for the entire handwritten sentence. Clearly, as shown in Figure 4, the
order used to write the delayed strokes change the shape of the whole word greatly. We can see that the same word with different orders of writing delayed strokes have two different shapes. Others approaches, like [Hu et al. (2000)], treat delayed strokes as special characters in the alphabet. So, a word with delayed strokes is given alternative spellings to accommodate different sequences where delayed strokes are drawn in different orders. But these two approaches are not practical as Arabic words may contain many delayed strokes. These methods will dramatically increase the hypothesis space, since words should be represented in all of their handwriting permutations. For example: the word ‘الحقيقة’ “the truth” contains 8 dots, thus, 8! representations would be required. As an example, Figure 5(a) show two different styles for writing the same word. In Figure 5(a) the writer wrote all the letters bodies then he wrote all delayed strokes. However, Figure 5(b) shows a different styles for writing the same word where writing delayed strokes is intermingled with writing the letters bodies. This shows that this approach is infeasible as it has to cover all possible handwriting representations of each word.

A fourth practical solution to handle delayed strokes is proposed by [Biadsy et al. (2006)]. The authors project the delayed strokes inside its related letter body by vertically projecting the first point of the delayed stroke into the overlapped letter body. The last point of the delayed stroke is connected to the following point in that letter body. This approach does not require any restrictions on the order of writing the delayed strokes which makes it practical but still has two shortcomings. Firstly, its requirement for the initial detection of the delayed strokes with possibilities of miss-detections. Secondly, there are cases where the delayed strokes appear before or after the word-part body where the delayed strokes will be connected to the closest word-part body. For example, Figure 6 shows a sample for this scenario. The shown word is /Tryq/ ”road” which start with the letter /TAH/. The delayed stroke overlap with the letter body and some part of it is written before the body itself. Hence, we can see that this approach will project the delayed stroke before the body itself. As a result, the system might confuse this letter with the two letters as they have the same shape. Moreover, as shown in Figure 5 the projection technique will harm regular characters that are not delayed strokes because they are totally overlapped.

3. Data Preparation and Acquisition

3.1. Preprocessing

The goals of the preprocessing phase are: reduce/remove imperfections caused by acquisition devices, smooth the irregularity generated by inexperienced writers having an erratic handwriting and minimize handwriting variations irrelevant for pattern classification which may exist in the acquired data. The preprocessing operations used in our system are:

- **Removing Duplicated Points**: Duplicated points are removed by checking whether the coordinates of any two points are the same. If so only one of them is kept.

- **Interpolation**: Applying linear interpolation to add any missing points caused by variation of writing speed ([Huang et al. (2007)]).

- **Smoothing**: To eliminate hardware imperfections and trembles in writing each point is substituted with the weighted average of its neighboring points ([Kavallieratou et al. (2002)]).

- **Re-sampling**: Due to the variation in writing speed, the acquired points are not distributed evenly along the stroke trajectory. This operation is used to get a sequence of points which is equidistant ([Kavallieratou et al. (2002)]).

- **De-hooking**: To remove the hooks that may appear with sensitive pens at the beginning or end of the strokes due to inaccuracies in rapid pen-down/up detection and erratic hand-motion

3.2. Delayed Strokes Rearrangement

The main harm of the delayed strokes is that they result in the scattering of the character components which does not match the expected sequence of the HMM model. So the motivation for our solution was to reorder the online strokes so the closer ones, in the geometric domain, come as successors in the time domain. But we found that the reordering operation is not only enough since some strokes can have several characters and the ideal order may need to insert some delayed strokes in the middle of those long strokes. So we decided to segment
the strokes into small segments then do the reordering operation on those small segments. At the end of each segment, a geometric condition is checked to make sure if a delayed stroke needs to be inserted. After doing all insertions needed, small segments are grouped again together if it is originally from the same stroke and no insertions happened between them. This way, we had the flexibility to do a finer reordering that allowed moving the delayed strokes as much as possible to their ideal location. When we applied that algorithm to our data, we managed to solve the delayed strokes problem in more than 96% of the cases. Even for the redundant multiple copies of the characters, their harmful effect was minimized. The delayed strokes reordering algorithm is presented Algorithm 1. The input to the algorithm is the set of the captured strokes from the handwriting text and a number that defines the size of a stroke segment (line 1); the rearranged strokes are added to OutputInk. Initially, all strokes are marked as not seen before then the algorithm loops through the whole strokes set (line 4-21) and try to reorder the delayed ones. If the stroke is not used (line 5-6), the stroke is segmented into small segments of the given size (line 7). After that, the algorithm loops through the whole set of segments while considering all the other input strokes (line 9-20). It checks if the current segment needs to be inserted in another stroke (line 17-19); if so, the segment order is considered and the algorithm reorder both stroke and the segment. Finally, after considering all strokes and segments, it returns the final ordered strokes.

**Algorithm 1 Delayed Strokes Rearrangement**

1: procedure RearrangeStrokes(Strokes: Array of input Strokes, N: NumberOfStrokes, S: Segment Size)
2:    OutputInk: Ordered Strokes
3:    Mark all strokes in Strokes as not used
4:    for StrokeCounter = 1 to N do
5:        if Stroke[StrokeCounter] is used then
6:            continue
7:    Segments =
8:        SEGMENT(STROKE(Strokes[strokeCounter], S))
9:    for SegmentsCounter = 1 to Segments.Size do
10:       for StrokeCounter2 = StrokeCounter + 1 to N do
11:          if Stroke[StrokeCounter2] is used then
12:              continue
13:          FPStr =
14:              GETFARTHESTPoint(Stroke[StrokesCounter2])
15:              GetFartestPointSegments[SegmentsCounter]
16:          if FPStr.x > FPStr.y then
17:              Add Stroke[segmentsCounter2] to OutputInk
18:              Mark Stroke[StrokesCounter2] as used
19:          Add Segment[SegmentsCounter] to OutputInk
20:          Mark Stroke[StrokesCounter] as used
21:    Return OutputInk

Figure 7 shows three examples of delayed stroke rearrangement. The legend located on the right side shows the order in which the strokes are written. The first sample shows how delayed strokes are handled in case of a single letter KAF which has a delayed stroke HAMZA. The delayed stroke will be inserted in its correct order in the middle of character body. In the second sample, for the original ink, we can see that the second written stroke colored with white green contains 4 delayed strokes. After rearrangement, this stroke is divided into sub strokes in order to have the delayed strokes inserted at their proper location.

To further show the effectiveness of our approach, we apply it on all the different cases discussed above. As we can see, it managed to reorder all the delayed strokes and insert them in their correct location. Figure 8 shows our results. Notice that, since we are grouping the strokes back after segmentation, if the algorithm did not detect any delayed strokes, the output from our algorithm will be exactly the same as the input (see the first two examples).

### 3.3. Feature Extraction

In our system we investigated many features and found the best set of features are as follows:

#### 3.3.1. Chain Code

Chain coding is one of the most widely used methods for boundary description, Wulandhari and Haron (2008). This code follows the boundary in counter clockwise manner and keeps track of the direction as we go from one contour pixel to the next. A 32-directional chain code is used in our system.

#### 3.3.2. Curliness

Curliness C(t) is a feature that describes the deviation from a straight line in the vicinity of (x(t), y(t)). It is based on the ratio of the length of the trajectory and the maximum side of the bounding box (Jaeger et al., 2001):

\[
C(t) = \frac{L(t)}{\max(\delta x, \delta y)} - 2
\]

where L(t) denotes the length of the trajectory in the vicinity of (x(t), y(t)), i.e., the sum of lengths of all line segments. \( \delta x \) and \( \delta y \) denote the maximum side of the bounding box.
and \( \delta x \) are the width and height of the bounding box containing all points in the vicinity of \((x(t), y(t))\). According to this definition, the values of curliness are in the range \([-1;N-3]\). However, values greater than 1 are rare in practice.

3.3.3. Aspect Ratio

The aspect of the trajectory is a feature which characterizes the height-to-width ratio of the bounding box containing the preceding and succeeding points of \((x(t), y(t))\). It is described as a single value \(A(t):\)

\[
A(t) = \frac{\delta y}{\delta x} - 1
\]

where \(\delta x\) and \(\delta y\) are the width and height of the bounding box containing all points in the vicinity of \((x(t), y(t))\).

3.3.4. Writing Direction

The local writing direction at a point \((x(t), y(t))\) is described using the cosine and sine functions as follows:

\[
\cos \beta = \frac{\delta x(t)}{\delta s(t)} \\
\sin \beta = \frac{\delta y(t)}{\delta s(t)}
\]

where \(\delta s(t)\), \(\delta x(t)\) and \(\delta y(t)\) are defined as follows:

\[
\delta s(t) = \sqrt{\delta x^2(t) + \delta y^2(t)} \\
\delta x(t) = x(t - 1) - x(t) \\
\delta y(t) = y(t - 1) - y(t)
\]

3.3.5. Curvature

The curvature of a curve at a point is a measure of how sensitive its tangent line is to moving that point to other nearby points. The curvature at a point \((x(t), y(t))\) is represented by the cosine and sine of the angle defined by the following sequence of points: \((x(t - 2), y(t - 2)), (x(t), y(t)), (x(t + 2), y(t + 2))\). Strictly speaking, this signal does not represent curvature but the angular difference signal. Curvature would be \(1/r\), of a circle touching and partially fitting the curve, with radius \(r\). Cosine and sine can be computed using the values of the writing direction:

\[
\cos \beta t = \cos \beta - 1 \ast \cos \beta + 1 + \sin \beta - 1 \ast \sin \beta + 1, \\
\sin \beta t = \cos \beta - 1 \ast \sin \beta + 1 - \sin \beta - 1 \ast \cos \beta + 1
\]

3.3.6. Baseline and Zones

This feature represents a vertical reference position for the characters and words in a handwriting sample. In our system it is determined using traditional histogram method by projecting the writing tracing points of a word or line of text onto a vertical line. The baseline is detected using the maximal peak in that histogram \(\text{[Huang et al. (2007)]}\).

After detecting the baseline, then the sample is divided into three zones upper, middle and lower according to its position from the baseline.

3.3.7. Loop detection

This is a Boolean feature, which indicate whether the current point is part of a loop or not. Figure 9 shows Arabic characters containing loops.

3.3.8. Hat feature

This feature indicates whether the current point is part of a delayed stroke or not. (i.e. the strokes that has been reordered using the previously described strokes reordering algorithm).

3.3.9. Extended Features

After geometric normalization, some extended sequences are derived from the basic function set. In our system, four dynamic sequences have been used as extended functions \(\text{[Fierrez and Ortega-GarciaH (2008)]}\), namely:

- Path-tangent angle
  \[
  \theta_n = \arctan y_n/x_n
  \]
- Path velocity magnitude
  \[
  v_n = \sqrt{x_n^2 + y_n^2}
  \]
- Log curvature radius:
  \[
  \rho_n = \log 1/k_n = \log v_n/\theta_n
  \]
where \(k_n\) is the curvature of the position trajectory and log is applied in order to reduce the range of function values.
- Total acceleration magnitude:
  \[
  a_n = \sqrt{t_n^2 + c_n^2}
  \]
where \(t_n = v_n\) and \(c_n = v_n \delta_n\) are respectively the tangential and centripetal acceleration components of the pen motion.

4. HMM Modeling of Handwriting

The proposed system is based on Hidden Markov Models (HMM). The HMM is a finite set of states, each of which is associated with a (generally multidimensional) probability distribution. Transitions among the states are governed by a set of probabilities called transition probabilities. Figure 10 shows a sample HMM model. Arabic contains 28 different letters, but as these letters are position dependent it will map to 103 different shapes. In our proposed system, we have 115 different models. These models include Arabic letters with their different shapes (103 models), 10 English digits (0-9), Arabic MAD symbol and English Capital V letter. This last two symbols were required.
for one of the evaluation databases we use (ADAB database). Also we built models for all the punctuation symbols.

In our system, we use left to right HMM model with different number of states per model according to how complex the model shape is. We use variable number of states varying from three to nine states. Three-States Models are the simplest models that consists of only a single straight stroke like the digit One ⌜ and the Arabic letter ⌜. Models with five states are more complex than the previous one as they contain either two strokes or they shape contain multiple transitions from horizontal to vertical and so on. Examples are ⌜, ⌜, ⌜ and ⌜. When shapes are getting more complex in terms of the number of strokes and the shape complexity, we model the characters with more states. For example, ⌜, ⌜ and ⌜ are modeled with seven states, whereas ⌜ ⌜ ⌜ and ⌜ are modeled with nine states.

Initially we built a mono-grapheme system which is based on the 115 different models mentioned above (position-dependent) using the Maximum Likelihood (ML) training [Fierrez and Ortega-Garcia (2008)] to maximize the probability of the training samples generated by the model. Then we expanded this initial model to a more sophisticated HMM model which is tri-graphemes context-dependent model. The tri-grapheme is a context dependent grapheme unit that considers both the preceding and following graphemes; for example the letter ⌜ in word part ⌜ is different from word part ⌜ although both of them is in the intermediate position. The tri-grapheme model expansion enables the precise modeling of the letters shape but with the price of the large increase of the models numbers. In our Arabic handwriting system with 28 different mono letters this would require (28)\(^3\) models. With this large number of models usually we don’t have enough database to train them. In our Arabic handwriting system we found that the required database to train these 20k models would be in the size of 8 million words while our training database included only 150k words. In order to deal with the problem of data insufficiency, we decided to cluster the HMM states to reduce the number of the trained models. We used a clustering technique based on decision trees. It is based on asking questions about the left and right contexts of each tri-grapheme and clusters together the states that have similar context. The questions that we used for the models clustering were derived from an analysis of the Arabic letters shapes and the different handwriting styles. For example one of the questions that we used ask about the cutting letters ([/ALF/], [/DAL/], [/REH/], [/ZEN/] and [/WAW/] and [/ZAL/]) which are the letters that have to be followed with the starting position letters. Also we clustered all the similar characters in shape such as [SEEN and SHEEN, SAD

and DAD ..etc. Figure 11 shows part of the decision tree that we used in our system.

4.1 Writer Adaptive Training

To train a robust writer independent handwriting system the training database should be collected from large number of writers. An inherent difficulty of this approach is that the resulting statistical models have to contend with a wide range of variation in the training data caused by the inter-writer variability. The features distributions will exhibit high variance and hence high overlap among the different grapheme units which may result in diffused models with reduced discriminatory capabilities. In speech recognition systems, Speaker A-daptive training (SAT) was developed to compensate for speaker differences during acoustic model training (Anastasakos et al. (1996)). Each speaker’s training data is linearly transformed so that it more closely resembles the training data for a prototype speaker. In this way, the models are made more precise, because the Gaussian doesn’t have to model inter-speaker variability-instead; inter-speaker variability is handled by a separate speaker normalization step, see figure 12.

Similar to the SAT training technique, a Writer Ada-ptive Training (WAT) technique is employed in our handwriting recognition system. We used Constrained Maximum Likelihood Linear regression (CMLLR) to adapt each training writer to the writer-independent model. CMLLR is a feature adaptation technique that estimates a set of linear transformations resulting statistical models have to contend with a wide range of variation during acoustic model training (Anastasakos et al. (1996)). Each speaker’s training data is linearly transformed so that it more closely resembles the training data for a prototype speaker. In this way, the models are made more precise, because the Gaussian doesn’t have to model inter-speaker variability-instead; inter-speaker variability is handled by a separate speaker normalization step, see figure 12.

Figure 10. HMM model sample

Figure 11. clustering questions
4.2. Discriminative Training

Historically, the predominant training technique for HMM has been the Maximum Likelihood Estimation (MLE). The MLE technique gives optimal estimates only if the model correctly represents the stochastic process, an infinite amount of training data is available and the true global maximum of the likelihood can be found. In practice, none of the above conditions is satisfied. This was the motivation for using discriminative training. The discriminative learning schemes such as Maximum Mutual Information (MMI), Minimum Word Error (MWE), Minimum Phone Error (MPE) and Minimum Classification Error (MCE) has recently gained tremendous popularity in machine learning since it makes no explicit attempt to model the underlying distribution of data and instead it directly optimizes a mapping function from the input data samples to the desired output labels. Therefore, in discriminative learning methods, only the decision boundary is adjusted without forming a data generator in the entire feature space (Zhou and He 2009).

In our system we increased the discrimination power of our models using a discriminative training scheme similar to the minimum phone error (MPE) approach. The training procedure is the same but we replaced the training unit to be a grapheme rather than the phoneme unit. The training criteria are:

$$F_{MGE}(M) = \sum_{H} \frac{P^{k}(O|H, M) P(H)}{\sum_{H} P^{k}(O|H, M) P(H)} A(H; H_{ref})$$  \hspace{1cm} (1)$$

Where $O$ is the observation sequence of the training utterance, $M$ is a model parameters and $H$ and $H_{ref}$ both denote possible hypotheses of the training data. $A(H; H_{ref})$ is the grapheme accuracy of the hypothesis $H$ given the reference $H_{ref}$. It equals the number of reference graphemes minus the number of errors. Two sets of lattices are needed: a lattice for the correct transcription of each training file, and a lattice derived from the recognition of each training file. These are called the numerator and denominator lattices respectively. Then the optimality criterion of equation (1) is used. In our system we name it the Minimum Grapheme Error (MGE), a one that tries to reduce the number of grapheme errors in the final result. Evaluation results show significant improvement of our system models after applying the discriminative training approach.

4.3. Gaussian Mixtures

In the final training step the Gaussian PDFs are converted into Mixture Gaussian PDFs. This process is done by splitting the Gaussians to increase their coverage for the features space. That process has to be done slowly, because any mixture Gaussian with number of mixtures larger than 1 suffers from spurious and undesirable global optimum parameter settings; i.e., if you try to learn a 128-component mixture Gaussian all at once without proper initialization, the training algorithm will learn a set of parameters that work really well for the training data and really badly for anything else, usually including at least one nearly-zero variance parameter. In order to avoid these effects, in our system training procedure we split the Gaussians gradually, e.g., going from one Gaussian to two, then to four, and so on, checking the variances at each step to make sure no variance parameter is getting too small (Gales 2001). We applied this gradual Gaussians splitting approach in our system and achieved much better performance than training all the Gaussians at once as shown in our system evaluation results.

4.4. Post-processing

In our HWR system we use a multi-pass decoding approach. Ideally, a decoder should consider all possible hypotheses based on a unified probabilistic framework that integrates all knowledge sources such as the HMM handwriting models and the language models. It is desirable to use the most detailed models, such as context-dependent models and high order n-grams in the search as early as possible. The Arabic language is extremely rich in inflections. As a result, a large dictionary is required to provide practical coverage for the language. When the explored search space becomes unmanageable, due to the increasing size of vocabulary or highly sophisticated knowledge sources, search might be infeasible to implement. A possible alternative is to perform a multi-pass search and apply several knowledge sources at different stages in the proper order to constrain the search progressively. In the initial pass, the most discriminative and computationally affordable knowledge sources are used to reduce the number of hypotheses. In subsequent passes, progressively reduced sets of hypotheses are examined, and more powerful and expensive knowledge sources are then used.

In our system we use two passes. In the first pass we use the most discriminant and computationally affordable knowledge sources which are word-internal tri-grapheme HMM model with bi-gram language model. The output of this first pass is a word lattice which represents a search space with reduced sets of hypotheses. This lattice includes several alternative words, and their HMM and language scores. Search might be infeasible to implement. A possible alternative is to perform a multi-pass search and apply several knowledge sources at different stages in the proper order to constrain the search progressively. In the initial pass, the most discriminant and computationally affordable knowledge sources are used to reduce the number of hypotheses. In subsequent passes, progressively reduced sets of hypotheses are examined, and more powerful and expensive knowledge sources are then used.

In our system we use two passes. In the first pass we use the most discriminant and computationally affordable knowledge sources which are word-internal tri-grapheme HMM model with bi-gram language model. The output of this first pass is a word lattice which represents a search space with reduced sets of hypotheses. This lattice includes several alternative words that were recognized at any given time during the search. It also typically contains other information such as the time segmentations for these words, and their HMM and language scores. In the second pass, we rescore this lattice with more powerful and expensive knowledge sources which are cross word tri-grapheme HMM model and a fifth-gram language model. To build this language model, we used a text corpus collected from crawling Aljazeera news website (alj). We collected around 700 MB of text containing 132 million words, each word is four characters on average. The language model is built using SRI
language modeling toolkit \cite{sril} with its default parameters. The lattice error rate is typically much lower than the word error rate of the single best hypotheses produced for each sentence. The multi-pass systems implementation is a successful approach to break the tie between speed and accuracy. With this approach it is possible to improve decoding accuracy with minor degradation in decoding speed.

5. Experimental Results

5.1. Small Vocabulary database

In the first evaluation the HWR system is evaluated against other state of art HRW systems. Only one international event was found for Arabic handwriting evaluation. This is the ICDAR conference that is based on the ADAB database. This database was developed in cooperation between the Institut fuer Nachrichtentechnik (IfN) and the Research group on Intelligent Machines (REGIM). The database consists around 20K samples written by more than 170 different writers, most of them selected from the narrower range of the National school of Engineering of Sfax (ENIS). The ADAB-database is divided to 4 sets. Details about the number of files, words, characters, and writers for each set 1 to 4 are shown in Table 1.

Preprocessing 2: Delayed Strokes Reordering, Resampling, Interpolation and Smoothing.

Preprocessing 4: Delayed Strokes Reordering, Resampling, Interpolation, Smoothing, Duplicate Points Removal and Dehooking.

From the results shown in Table 5 we can see how promising our system performance compared to the state of the art systems. Results show that the Delayed Strokes Reordering is an essential operation in the system. Also the other utilized preprocessing operations have provided absolute 1.8% improvement in the system accuracy. The used advanced training techniques provided another 2.2% improvements in accuracy. It is worth mentioning here that all the experiments in Table 4 are using the same feature set defined in Section 5.3.

5.2. Large Vocabulary

Our second concern was evaluating our system in a large vocabulary task. We evaluated the system using the ALTEC Arabic Handwriting (ALTECOnDB) database \cite{altec}. This database contains handwriting samples from 1000 different writers comprised of men and women from various professional backgrounds, qualifications, and ages. Each writer was asked to write 4 pages that contains 200 words on average. The written text was selected from the Gigaword Arabic text database. A 30K sentences were used to train the language modeling tool. The ALTEC-AH test set contains 200 words on average. The written text was selected from that database with 99% coverage of the paws of the Arabic language. Table 4 show the statistics of the ALTECOnDB database.

For system testing we used the ALTEC-AH test set. This test set is collected by 16 writers. Each writer wrote 11 pages with average 750 words. The Out Of Vocabulary (OOV) ratio for this test according to a 64k dictionary is 8.3%. Detailed statistics are shown in Table 5.

| Table 1. ADAB Database Characteristics |
|----------------------------------------|
| Set | Files | Words | Characters | Writers |
|-----|-------|-------|------------|---------|
| 1   | 5037  | 76150 | 97600      | 56      |
| 2   | 5090  | 7851  | 97615      | 37      |
| 3   | 5051  | 7730  | 80544      | 39      |
| 4   | 4417  | 6911  | 35253      | 41      |

| Table 2. ADAB Set4 results (ICDAR 2009) |
|----------------------------------------|
| System      | Method      | Top 1 | Top 5 | Top 10 |
|-------------|-------------|------|------|--------|
| MDSLSTM-1   | NeuralNet   | 95.70| 98.93| 100   |
| MDSLSTM-2   | NeuralNet   | 98.93| 100  | 100   |
| VisionObjects-1 | NeuralNet    | 98.99| 100  | 100   |
| VisionObjects-2 | NeuralNet    | 98.99| 100  | 100   |
| REGIM-HTK   | HMM         | 52.67| 63.44| 64.52 |
| REGIM-Cv    | VC          | 13.99| 31.18| 57.83 |
| REGIM-Cv HTC | HMM&VC      | 38.43| 59.30| 69.89 |

| Table 3. System evaluation for the ADAB Database |
|----------------------------------------|
| System                                | Top 1 | Top 5 | Top 10 |
| Mono-Grapheme + No Preproc            | 2.15  | 4.08  | 14.49  |
| Mono-Grapheme + Preproc 1             | 92.66 | 97.85 | 98.50  |
| Mono-Grapheme + Preproc 2             | 93.52 | 97.92 | 98.39  |
| Mono-Grapheme + Preproc 3             | 93.79 | 97.92 | 98.60  |
| Mono-Grapheme + Preproc 4             | 94.43 | 98.52 | 98.92  |
| Writer Adaptive Training              | 94.83 | 98.56 | 98.91  |
| Discriminative Training               | 95.98 | 98.42 | 99.17  |
| Tri-Grapheme                          | 98.18 | 98.90 | 99.13  |
| Quad-Graphemes                         | 99.13 | 99.13 | 99.40  |

| Table 4. ALTEC database statistics |
|-------------------------------------|
| Total Number | Unique entries |
| 152680 | 39945 |
| 325477 | 134140 |
| 4512 | 1066 |

| Table 5. ALTEC-AH test set statistics |
|---------------------------------------|
| Number of writers | 16         |
| Number of pages   | 176        |
| Number of lines   | 1717       |
| Number of Words   | 12853      |
| OOV words          | 1066       |
We generated a writer-dependent models from the writer-independent ones using the CMLLR technique discussed before. The writer-dependent models are created for the different writers in the test set by splitting the test set ALTEC-AH into adaptation part and testing part. For each writer in the test data, we used only 4 pages for the model adaptation. The rest 7 pages are used for evaluating the writer-dependent models.

In this experiment, we show the performance of our system, both writer-independent and dependent models, using two passes:

- **Pass 1**: uses the same trained models used for evaluating ADAB database but with a a larger dictionary of size 64K words.
- **Pass 2**: The output of the first pass is a lattice which includes several alternative words that were recognized at any given time during the search. It also typically contains other information such as the time segmentations for these words, and their HMM and language scores. In the second pass, we rescore this lattice with a high-level (five-grams) linguistic model to improve the performance of the first pass.

Table [6] shows the evaluation results of our system for the ALTEC-AH test set. We can see that our results are very promising. After the second pass of the writer-independent models, the system’s accuracy increased from 68% to 80%. For the writer-dependent models, the system acheived an accuracy of 79.4% in pass 1 which increased to 87.5% after using the high-order language model. Notice that, after adapting the system models to match the writing style and characteristics of the system users, our system could boost the accuracy to 87.5% and this was achieved with an amount of adaptation data less than 200 words per writer. The streamed output results of the system, i.e the immediate partial results without waiting for writing the whole sentence, are only 79% for the adapted system and 68% for the writer independent system which is still not a practical accuracy. If we exclude the OOV words from our evaluation results the in-vocabulary accuracy is 87% for the writer-independent system and 95% for the adapted system. We did not find any references for reported results on comparable large vocabulary Arabic handwriting systems to compare our system against them.

## 5.3. Runtime

In this experiment, we report the average time it takes our system to recognize a sample. All experiments are run using a Lenovo z560 laptop with 4G RAM and 2.53GHz Intel core i5 processor. The laptop is running 64-bit Microsoft Windows 7.

Table [7] shows the time it takes our system on average to recognize ADAB Set4 samples. A sample can be a single or few words. We report the average time it takes our system to output the top 1, 5 and 10 results respectively. As we can see, when supporting small vocabulary, our system is almost real-time. It takes less than a second to produce the full top 10 matches of a given sample.

In Table [8] we report the running time of our system when working on large vocabulary. As expected, as the supported vocabulary size increases, our system takes more time (2.2 seconds) to recognize a test sample. Although, Pass 2 takes very small time (0.15 seconds) to rescore the produced lattice from Pass 1, it managed to get significantly more accurate results as shown in Table [6].

## 6. Conclusion

We proposed a system for large-vocabulary Arabic online Handwriting recognition that provides solutions for most of the difficulties inherent in recognizing the Arabic script. A new approach for handling the delayed strokes is introduced which avoids the drawbacks of the previously introduced methods in literature. Our system is based on Hidden Markov Models and trained with advanced modeling techniques adopted by speech recognition systems such as context dependent modeling, speaker adaptive training, discriminative training and Gaussians mixtures splitting. The system results are enhanced using an additional post-processing step to rescore multiple hypothesis of the system result with higher order language model and cross-word HMM models.

Our HWR system outperforms state-of-the-art research efforts when evaluated using a data set with a small vocabulary. Furthermore, when tested on a large vocabulary database (ALTECOnDB), the results we obtained are very promising in terms of both accuracy and running time. The advantage of our system is its simple structure, and its adopted models are based on mature technology for sequential data modeling. With only few data samples, the writer independant models can be adapted for a certain writer to acheive better accuracy. In the future work, we plan to expand the system vocabulary up to half million words to reach 99% coverage of the Arabic language. This would require the investigation of using some of the fixed search decoding techniques such as finite state decoders.

### References

- Aljazeera.net, [http://Aljazeera.net/](http://Aljazeera.net/)
- SRILM - The SRI Language Modeling Toolkit, [http://www.speech.sri.com/projects/srilm/](http://www.speech.sri.com/projects/srilm/)

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| Table 6. System evaluation - ALTEC-AH | Table 7. Small Vocabulary Running Time (ADAB Database) | Table 8. Large Vocabulary Running Time (ALTECOnDB) |
|--------------------------------------|--------------------------------------|--------------------------------------|
| System                              | Pass1 Accuracy | Pass2 Accuracy | Database | Average time per sample(seconds) | Average time per word(seconds) |
| Writer-Independent                  | 68.76         | 80.07         | ADAB Set 4 | 0.448     | 0.937x |
| Adapted models                      | 79.40         | 87.47         | ALTEC-AH  | 2.3       | 0.15  |

| Database | Top 1 | Top 5 | Top 10 |
|----------|-------|-------|--------|
| ADAB Set 4 | 0.448 | 0.937x | 0.923 |
| ALTEC-AH | 2.3 | 0.15 | 87.47 |
