Arabic Handwritten Word Recognition based on Dynamic Bayesian Network

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Abstract: *Distinguishing an Arabic handwritten text is a hard task because the Arabic word is morphologically complex and the writing style from one model is highly variable, like the recognition of words representing the names of Tunisian cities. Actually, this is the first work based on the Dynamic Hierarchical Bayesian Network (DHBN). Its objective is to get the best model by learning the structure and parameter of Arabic handwriting to decrease the complexity of the recognition process by allowing the partial recognition. In fact, we propose segmenting the word based on a vertical smoothed histogram projection using various width values to put down the segmentation error. After that, we extract the characteristics of each cell using the Zernike and HU moments, which are invariant to rotation, translation and scaling. Then, the sub-character is estimated at the lowest level of the Bayesian Network (BN) and the character is estimated at the highest level of the BN. The overall Arabic words are processed by a dynamic BN. Our approach is tested using the IFN/ENIT database, where the experiment results are very promising.*

Keywords: *Arabic handwriting recognition, dynamic BN, hierarchical model, OCR, IFN/ENIT databases.*

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1. Introduction

The term handwriting recognition is used most often to describe the capability of a computer to transform human writing into text. It has many applications in many fields such as bank-check processing, post-address interpretation, document archiving, mail sorting and form processing in administration and insurance [2, 3, 4, 12, 15, 17]. The handwriting recognition can be divided into two categories: The online recognition and the off-line one. In the online case, temporal information like the pen-tip coordinates as a function of time is available [6] so; it makes it easier than the offline case. In addition, the offline handwriting recognition has many problems that can be divided into two significant research areas: Segmentation and recognition [14, 19, 21]. These two areas are very difficult tasks especially in Arabic handwriting due to the cursive nature of the Arabic script and the different handwriting styles and uncertainty of human writing and other problems such as overlapping of some pseudo-words, fusion of diacritical marks in different position in the word, shape discrimination and variation, scanning methods, writing discontinuity and slant. In this work, we propose a novel approach that reduces the segmentation step's error and increases the recognition accuracy. The recognition step is preceded by a feature extraction process that extracts the characters and sub-character features from the segmented word. In the segmentation step, we have used a smoothed vertical histogram projection with different width values to minimize the segmentation error.

The overall system diagram is shown in Figure 1. Our system processes multiple analysis levels.

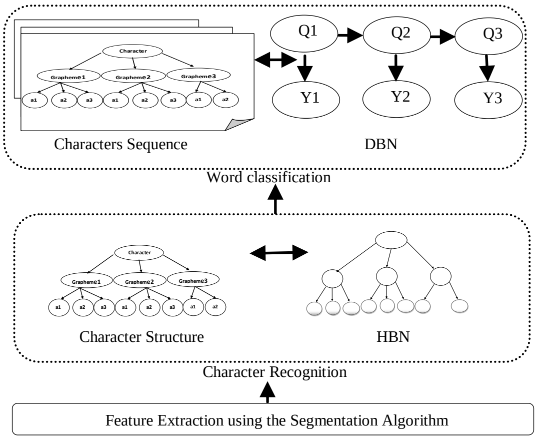

Figure 1. System diagram.

The character features are extracted from our developed segmentation system; afterwards, they are used to estimate our character class using the Bayesian Network (BN). The class of character results is then concatenated to form a sequence and the sequence classification is performed by a Dynamic Bayesian Network (DBN). In the character class estimation step, the left panel shows a tree structure that represents the bloc character of the word. The root node represents the character class and its children nodes represent the frame generated by a uniform sliding window. Each frame is subdivided into cells. The right panel shows a BN to estimate the character class in each bloc. In the sequence classification stage, the left panel shows the word sequence represented by the concatenation of three tree structures representing a character at each frame. The right panel shows a DBN which recognizes the word image.

The contributions of this paper are as follows: A new hierarchical framework is detailed for the recognition of the off-line Arabic handwritten word using the Hierarchical Bayesian Network (HBN), a stochastic graphical model is proposed for the word recognition and a combined system that balances between segmentation and recognition is used to match and reduce the segmentation error to have a higher recognition rate. The rest of the paper is divided as follows. In section 2, we describe the works related to our research. Section 3 presents the developed system and the concepts of the Dynamic Hierarchical Bayesian Networks (DHBNs). In section 4, we describe the experimentations and results. Finally, we present the discussion and conclusions.

2. Related Works

A review of the literature indicates that relatively limited applications, based on BNs and DBNs, have been developed for the handwriting recognition. We state the main works in what follows.

Hallouli *et al.* [10] developed a new probabilistic model designed for the off-line printed character recognition based on the DBN. Their system was evaluated using various DBN architectures and achieved a recognition rate of 98.3% with the vertical HMM and 93.7% with the horizontal one. Nevertheless, when testing degraded letters, the recognition rate went down to 93.8% with the vertical HMM and 88.1% with the horizontal one.

Also, Mahjoub *et al.* [18] proposed a new system for the offline handwritten Arabic word recognition based on coupled HMMs, considered as a single DBN. Each image of the handwritten word was transformed into two sequences of feature vectors that would be the observations to be given to the DBN model. The developed system was tested on the IFN/ENIT database and achieved a recognition rate between 67.9% and 77.4%.

Al-Hajj *et al.* [2] presented a system for the off-line recognition of handwritten Arabic city names. The system combined three homogeneous HMMs having the same topology as a reference system which differed only in the orientation of the sliding window. The results showed that the combination of classifiers would perform better than a single classifier dealing with slant-corrected images and that the approach was robust for a wide range of orientation angles.

Benouareth *et al.* [6] proposed an offline unconstrained Arabic-handwritten-word recognition system based on a segmentation-free approach and on discrete Hidden Markov Models (HMMs) with an explicit state duration. The system applied a sliding window approach and extracted a set of statistical and structural features. Several experiments were performed using the IFN/ENIT and the recognition rate, saved with a non-uniform segmentation, was better than the uniform one.

Parvez and Mahmoud [25] suggested an off-line Arabic handwritten text recognition system using structural techniques. The Arabic word image was pre-processed. Then, a segmentation algorithm was integrated into the recognition phase of the handwritten text. The recognition of the Arabic PAWs was done using a novel fuzzy polygon matching algorithm. This proposed system was tested using the IFN/ENIT database and the recognition rate achieved was promising, which was about 79.58%.

Alkhateeb [5] developed a multi-classification system based on the DBN. First, the words were pretreated and normalized. Then, a two uniform sliding window were used to segment the word image in a horizontal and vertical direction in order to extract the corresponding features. After that, several coupled-HMM architectures, viewed as a single DBN, (see Figure 2), were constructed by adding directed edges between the two streams within the same time slice in different ways. Their suggested system has been successfully tested on the IFN/ENIT database and the results were promising.

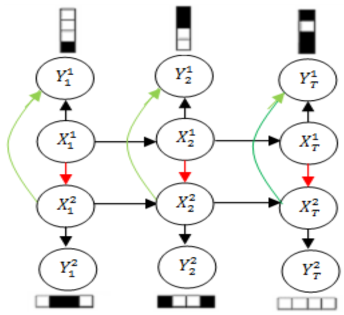

Figure 2. Coupled architecture representing a single DBN [5].

In contrast to Alkhateeb, we have proposed, in this work, a hierarchical model based on the DHBNs to recognize an offline Arabic-handwriting word. First, after the preprocessing step, we have segmented the word into characters and sub-characters using the smoothed vertical histogram projection. Then, each character has been segmented using a uniform sliding window into 3 frames divided into 2 cells. Finally, we have extracted the HU and Zernike moments for each cell and used it to train our constructed HDBNs. In fact, the advantages of such a model consist in finding the best model of Arabic handwriting to reduce the complexity of the recognition process by permitting the partial recognition. This model has made good results in the human interaction domain, but by analysing the literature, it has never been used in the Arabic-handwriting recognition.

3. System Architecture

The system architecture that we have proposed to the recognition of offline handwritten Arabic city names is based on the DHBN as shown in Figure 3. It contains fives stages in terms of pre-processing, segmentation, feature extraction, vector quantization and learning and classification. The first step is the pre-processing; it consists in normalizing the image. After that, the word is segmented, using our proposed non-uniform segmentation, into characters. Then, these characters are segmented, using a uniform segmentation, into graphemes. In the third step, we extract the reliable features to characterize these graphemes. The use of the discrete DBNs as a classifier is necessary to process to the next step to quantize these ones. In the fourth step, we have trained and optimized our model to use it in the classification step.

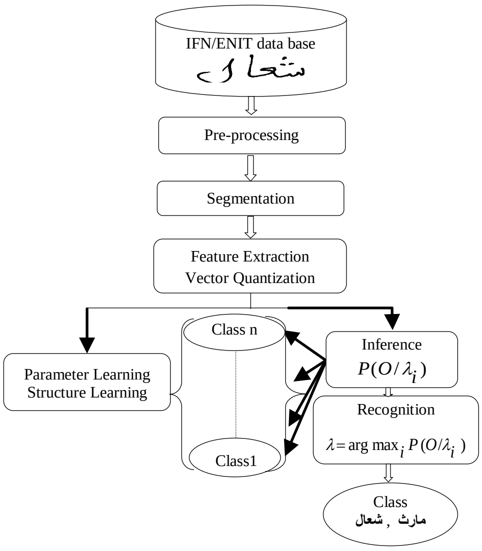

Figure 3. The proposed block diagram system for word recognition.

3.1. Pre-Processing and Segmentation

The aim of the pre-processing step is to enhance the word image to have a better segmentation and so increase the recognition rate. The pre-processing chain of the recognizer starts out with some of the usual operation such as: Thinning, remove horizontal and vertical space and the diacritical marks. As it is well known, the segmentation is a very hard step in Arabic-handwritten-word recognition because of its high variability and the complex morphology of Arabic as a semi cursive script. So, we have introduced, in the next step, a non-uniform segmentation based on the vertical histogram projection to segment the word into characters. To solve the problem of over or under segmentation of a word, we have proposed to use a heuristic. It consist in smoothing the vertical projection histogram to give us the best number of frames, which have to be the same as the number of characters in the word, and the best boundaries of each characters for each model. After that, we segment the character into frames and cells using a uniform segmentation. The number of frames is fixed empirically, yielding the highest recognition rate, to 3 and the number of cells to 2. The pre-processing and segmentation algorithm is detailed as shown in Algorithm 1:

Algorithm 1: Pre-Processing and segmentation algorithm.

For k=1 *to number of images of each word*
Begin
Img_in=Read the binary image.
Img_in=Resize the Img_in into 100×200.
Img_in=Remove the horizontal and vertical space from image.
Img_in_Diac=Remove the diacritical marks from Img_in.
Blocks_Limit=Segment the image word into characters by finding the best boundaries of each character using the peaks of the smoothed vertical histogram projection of Img_in_Diac.
The optimal value of the width of smoothing is determining empirically giving us the best number of frames.
Block_Charact= Divide the Img_in using each Blocks_Limit into characters. Then, we divide each characters into 3 *uniform horizontal frames and each frame into* 2 *uniform cells.*
end

3.2. Feature Extraction and Vector Quantization

Feature extraction is an important step in the handwritten recognition. The choice of feature sets should be independent to the size, orientation and location of the pattern. So, with referring to the literature, we have extracted for each cell the moment invariant of Zernike and HU which are invariant to translation, rotation and scaling, to check the primitives of each character. Nevertheless, the descriptors of these moments give us continuous features. However, we use discrete DBNs, so we have to process to the next step of pre-treatment, which consist in quantizing each continuous feature vector representing a cell to a discrete symbol. This quantization is done by k-means method. The k-means method aims to cluster the feature vector of the training samples into several classes. Each one is represented by its centroîd which is a 17 dimensional vector. After that, the index of each centroîd is considered as a codebook symbol. For each model, we have chosen the optimal codebook using a validation data set.

3.3. Classification

The DBNs are a class of temporal graphical probabilistic models that have become a standard tool for modelling various stochastic time varying phenomena. The temporal probabilistic graphical models as two-time BNs are the most used and popular models for the DBN. Before introducing the notion of the DBN, we will briefly recall the definition of the BN.

3.3.1.Bayesian Network

- ***Definition***: A static BN combines between the graph theory and probability theory. Thus, a BN consists of a Directed Acyclic Graph (DAG) whose nodes are random variables that may have a discrete number of possible states or continuous values.

  The BN is defined by:
- A *DAG G*= (*V*, *E*), where *V* is a set of nodes of *G* and *E* is a set of arcs of *G*.
- A finite probabilistic space (*Ω*, *Z*, *p*).
- A set of random variables associated with graph nodes and defined on (*Ω*, *Z*, *p*) as:

$$p(V_1, V_2, \dots, V_N) = \prod_{i=1}^{N} p(V_i \mid C(V_i)) \qquad (1)$$

Where $C(V_i)$ is a set cause [parents] V_i in the graph *G*.

3.3.2. Hierarchical Bayesian Network

The HBNs are a generalization of the static BNs, where a node in the network may be an aggregate data type. This allows the random variables of the network to arbitrarily represent structured types. Within a single node, there may also be links between components, representing probabilistic dependencies among parts of the structure. The HBNs encode the conditional probability dependencies in the same way as the static BNs as shown in Figure 4.

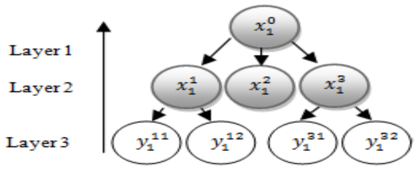

Figure 4. HBN with three layers.

3.3.3. Dynamic Hierarchical Bayesian Network

The DHBNs are an extension of the static HBNs which represent the temporal evolution of any random variable. Thus, a dynamic BN is a chain of the same BN repeated as many times as needed. The temporal dynamics are represented by arcs connecting the various static BNs between each other Figure 5. The construction of a DHBN requires determining its structure and its parameters. So, to specify a DBN [23] we need to define the intra-slice topology (within a slice), the inter-slice topology (between two slices) and the parameters for the first two slices as explained in the next section.

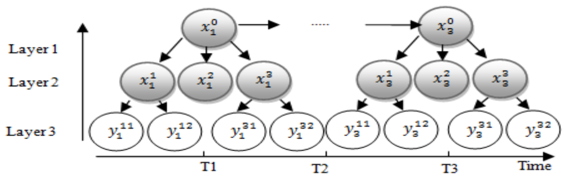

Figure 5. DHBN for a word image composed of three characters.

3.3.4. Inference and Learning in DBN

This particular DBN is equivalent to a traditional HMM because it emulates what an HMM does. One major difference is that it explicitly represents the HBN consistence of the word, character and sub character.

- *Structural Learning*: Description of settings.

$$X_t = \left\{x_t^0, x_t^1, \ldots, x_t^N\right\} \tag{2}$$

Is a set of the hidden state in the time *t*, where *N* is the number of the latent states in one slice.

$$Y_t = \left\{ \begin{array}{l} \left\{y_t^{11}, y_t^{12}, \ldots, y_t^{1M^1}\right\}, \left\{y_t^{21}, y_t^{22}, \ldots, y_t^{2M^2}\right\}, \ldots, \\ \left\{y_t^{N1}, y_t^{N2}, \ldots, y_t^{NM^N}\right\} \end{array} \right\} \tag{3}$$

Is a set of the observed state in the time *t*, where each state has two observed states, with $M^j \forall j \in [1, N]$ being the number of the observed state of each latent state. We can assume that the set of:

$$Y_t = \left\{Y_t^1, Y_t^2, \ldots, Y_t^N\right\} \tag{4}$$

$\pi = \left\{\pi_i\right\}$: The initial state probability.

$$\pi_i = P(X_1 = i) = \prod_{i=1}^{N-1} P(x_1^j = j \mid x_1 = i), 1 \prec i \prec N \tag{5}$$

$A = \left\{a_{ij}\right\}$: The state transition probability.

$$a_{ij} = P(x_t = j \mid x_{t-1} = i), 1 \prec i, j \prec T \tag{6}$$

$B = \left\{b_j(k)\right\}$: The observation probability distributions.

$$b_j(k) = P(Y_t = k \mid X_t = j) = \prod_{i=1}^{N} P(Y_t^i = k \mid X_t = j) \tag{7}$$

- *Parameter Learning:* More succinctly, a DHBN can be represented by the parameter $\lambda=(A, B, \pi)$. To suitably use the DHBN in the handwriting recognition, three problems must be solved. The first is concerned with the probability evaluation of an observation sequence, given the model λ. In the second problem, we attempt to determine the state sequence that best explains the input sequence of observations. The third problem consists in determining the method to optimize the model parameters to satisfy a specific optimization criterion. The model parameter determination is usually done by the Expectation/Maximization procedure and consists in iteratively maximizing the observation, given the model and often converges to a local maximum. As the DBN usually captures the joint distribution of the variable sequence, it is typically learned by maximizing the log likelihood of the training sequence $\theta_{MLE}=argmax_\theta P(Y/\theta)$.
- *Inference and Recognition*: The simplest inference method for a discrete-state DBN is to convert it to an HMM and then to apply the forward-backward algorithm. Therefore, the probability $P(O/\lambda)$ of a DBN model with an explicit state duration, for an observation vector sequence using the length of the observation sequence for each *t* slice, can be computed by a generalized forward-backward algorithm. This choice is justified by the availability of the estimation formulas, which are derived with respect to the likelihood criterion, for the parameter set of the distribution. In the recognition phase, a solution to the state decoding problem, based on dynamic programming, has been designed, namely the Viterbi algorithm. The sequence of the extracted feature vectors is passed to a lexicon network formed of word models.

4. Experimental Results

In the following section, we will present the experimental results done using a lexicon from the IFN/ENIT data base. The conducted experiments are compared with the other system. The results are presented below in detail.

4.1. IFN/ENIT Database

The IFN/ENIT data base consists of 946 handwritten Tunisian city names and their corresponding postcodes. The old version (v1.0p2 version) of the database contains 26,459 Arabic names handwritten by 411 different people. In the new v2.0 p1e version, the additional set e containing 6,033 names handwritten by 87 writers has been added, which makes the whole set have 32,492 name samples. In the last new version, two additional sets have been added: set f containing 8,671 names and set s containing 1,573 ones. Relevant experiments and results are presented in the next subsections.

4.2. Experiments on IFN/ENIT Database v1.0p2

In this group of experiments, three subsets (a-c) are used for training and validate the DHBN and another one (d) for testing. After pre-processing, the optimal width of the smoothed histogram is determined empirically using different numbers varying from 8 to 15. We have chosen the width that provides a number of characters that reflects better the number of characters in the model. After segmenting the word into characters, we divide the character block into 3 frames and each frame into 2 cells. We have chosen the frame and cell number that provides the highest recognition rate. Then, an optimal number of states used in the DBN is also determined empirically. Using possible numbers varying equally from 10 to 25, the obtained recognition rates are listed in Figure 6. It has been noted that the recognition rate improves as the number of the states increases to reach the maximum possible state for a specific feature set. This makes the training data independent from the testing data, hence avoiding over-fitting the classifier to test the data. In our case, as shown in Figure 6, the optimal state number of class c3 is found as 21 and of the class c4 is found as 13.

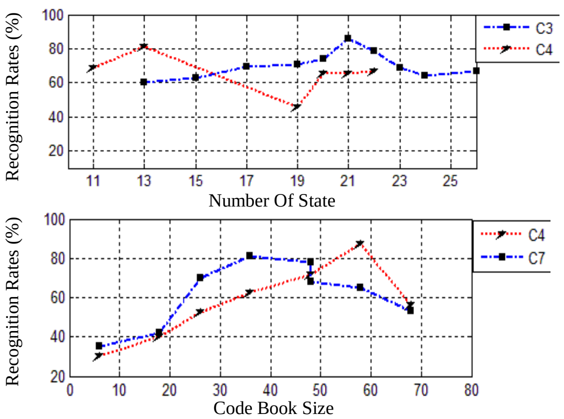

Figure 6. Recognition rate vs number of state and code book size.

In this paper, a DBN has been used for the Arabic handwritten word. Each character is represented by its feature vector and each character requires a number of observations for training and testing the DBN. In the phase of quantizing the data, experiments have been conducted using 7 codebook size parameter values: 6, 18, 24, 36, 48, 58, 68 and 100. Figure 6 shows the result for a different codebook size that yields to a better recognition rate of a ‘شماخ’ and ‘الرضاع’ class. The best performance has been found using the number of observation sizes which is 58 for C4 and 38 for C7 to obtain a good trade off between the best recognition accuracy and the low time factor.

Figure 7 shows the experimental results of the performance evaluation of our recognition system using the training set (a-c) and the test set (d). This leads to an average recognition rate of about 91.25%, which is achieved with the training set and of about 82% which is achieved with the test set.

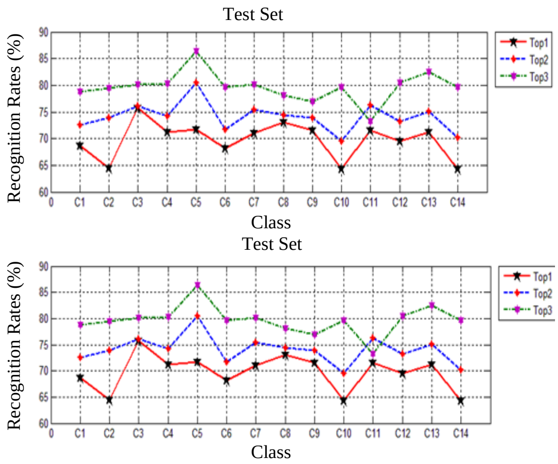

Figure 7. Recognition rates obtained by training and test set for some classes.

Table 1 gives the comparative results on set d of the IFN/ENIT database.

Table 1. Comparative study using v1.0p2 database.

Authors	Classifier	Training Data	Test Data	Recognition Rate	
				Top1	Top 10
Al-Hajj *et al.* [2]	HMM	Set a-c	Set d	87.6	93.76
Benouareth *et al.* [6]	HMM	Set a-c	Set d	83.79	92.12
Dreuw *et al.* [7]	HMM	Set a-c	Set d	89.22	Unknown
El-Abed and Margner [20]	HMM	Set a-c	Set d	89.1	96.4
Al-Hajj *et al.* [1]	HMM	Set a-c	Set d	75.41	Unknown
Menasri *et al.* [22]	HMM/ANN	Set a-c	Set d	87.2	Unknown
Pechwitz and Margner [24]	HMM	Set a-c	Set d	89.74	94.98
Alkhateeb *et al.* [3]	HMM	Set a-c	Set d	86.73	93.68
Kundu *et al.*[16]	Variable Duration	Set a-c	Set d	60	Unknown
Proposed System	DBN	Set a-c	Set d	82	Unknown

4.3. Experiments on v2.0p1e IFN/ENIT Database Version and Comparative Study

We present now our results on set e of the IFN/ENIT database. In this group of experiments, four subsets (a-d) are used for training and validate the DHBN and set e for testing; we have achieved a word recognition accuracy of 78.5%. Figure 8 illustrates the recognition rates obtained by test set e for some classes.

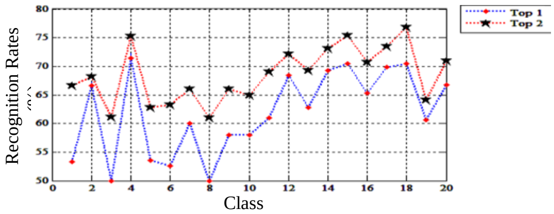

Figure 8. Recognition rates obtained by test set e for some classes.

Table 2 gives the comparative results on set e of IFN/ENIT database. A detailed analysis of the results is given below.

Table 2. Comparative study using the v2.0p1e database.

Authors	Classifier	Training Data	Test Data	Lexicon Usage	Recognition Rate	
					Single-Classifier	Multi-Classifiers
Elbaati *et al.* [8]	HMM	Set a-d	Set e	Not mentioned	54.13	
Margner *et al.* [20]	HMM	Set a-d	Set e	yes	74.69	
hamdani *et al.* [11]	Multiple HMM	Set a-d	Set e	Not mentioned	49-63	81.93
Kessentini *et al.* [13]	Multi-stream HMM	Set a-d	Set e	yes	63.5-70.5	79.6
Parvez *et al.* [25]	FATF with set-medians	Isolated characters	Set e	yes	79.58	
Giménez *et al.* [9]	windowed Bernoulli HMMs	Set a-d	Set e	Not mentioned	84	
Proposed System	DBN	Set a-d	Set e	yes	63-78.5	

As it can be noted from Tables 1 and 2, the proposed system is the first attempt to experiment with the IFN/ENIT database with the DBN. Most of the previous results on the IFN/ENIT database are based on HMM. Tables 1 and 2 also show the training and test sets used by the other researchers. The authors given in Table 1 had trained their systems on sets a-c and tested on set d, and those given in Table 2 had trained their systems on sets a-d and tested on set e.

4.4. Discussion

The developped system has some error rate like the other proposed approach in this field. In fact, due to the cursive nature of Arabic handwritten as script and its variability, we evoke the following reasons. The first one is related to the high variability of Arabic handwritten word caused by many factors such as the variations of shapes come from the human writing habit, style and condition. In addition, we find the cause related to the fusion of diacritical marks, writing instrument, touching of word and sub-words. For instance, if one word contains samples in various writing styles/forms or different words share one similar shape, it inevitably leads to misclassification. The second one is linked to the process of pre-processing and word segmentation as the descenders of a letter and the diacritical marks are often not at the exact position on top or under the main part of the letter. Those errors will be propagated and lead to an inexact feature extraction due to a wrong word boundary and/or inaccurate extraction of topological features coming from an over or under segmentation. To reduce these error and so improve the performance of the system, we can ameliorate the pre-processing step by baseline location or slant correction. Similarly, each word has a number of characters which has the same length as of the inter-slice, so that it may participate in the error of the recognition rate. Finally, the inequitable frequence of some words in the data base affects its correct recognition. In fact, some words has more occurrence represented by a few hundreds of samples. However, others words are reprenseted by three samples (even absent) in the training data.

5. Conclusions

We have proposed a new approach for the offline Arabic handwritten word recognition based on the DHBN using a free segmentation released by a smoothed vertical projection histogram with different width values. The model is consist of three levels. The first level represents the layer of the hidden node which models the character class. The second layer models a frame set representing the sub-characters, and the third layer models the observation nodes. The developed system has been experimented and the results are provided on a subset of the IFN/ENIT benchmark data base. These results show a significant improvement in the recognition rate because of the use of the DHBN. Most of the recognition errors of the proposed system can be attributed to the segmentation process error and to the poor quality of some data samples. In addition, some character shapes are insufficiently represented in the database. As a consequence, their models are badly trained.

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