ISSN 2047-3338

The State of the Art Handwritten Recognition of Arabic Script Using Simplified Fuzzy ARTMAP and Hidden Markov Models

Yusuf Perwej[1], Shaikh Abdul Hannan[2] and Nikhat Akhtar[3]
[1,2]Department of Computer Science & Engg., Al Baha University, Al Baha, Kingdom of Saudi Arabia (KSA)
[3]Department of Computer Science & Engg., Integral University, Lucknow, India
[1]yusufperwej@gmail.com, [2]abdulhannan05@gmail.com, [3]dr.nikhatakhtar@gmail.com

***Abstract*– In this paper, we present recognition of handwritten characters of Arabic script. Arabic is now the 6th most spoken language in the world and is spoken by more than 200 million people worldwide. The 7th Century A.D., Arabic started to spread to the Middle East as many people started to convert to Islam. During this time of religious conversions, Arabic replaced many South Arabian languages, most of which are no longer commonly spoken or understood languages. The challenges in Arabic handwritten character recognition wholly lie in the variation and disfigurement of Arabic handwritten characters, since different Arabic people may use a different style of handwriting, and direction to draw the same shape of the characters of their known Arabic script. Though various new propensity and technologies come out in these days, still handwriting is playing an important role. To recognize Arabic handwritten data there are different strategies like Simplified Fuzzy ARTMAP and Hidden Markov Models (HMM). In this paper, we are using Simplified Fuzzy ARTMAP, which is an updated version of Predictive Adaptive Resonance Theory. It also has a capacity to adjust clusters, as per the requirements Arabic script, which is remunerative to mitigate noise. We have tested our method on Arabic scripts and we have obtained encouraging results from our proposed technique.**

***Index Terms*– Hidden Markov Model (HMM), Arabic Script, Handwriting, Fuzzy ARTMAP, Recognition and Feature Extractor**

I. INTRODUCTION

ARABIC is the official language of many countries in the Middle East such as Saudi Arabia, Jordan, Lebanon, Libya, Egypt, Iraq, Morocco, and Sudan. It is also one of the six official languages of the United Nations. Arabic is a “Semitic,” language and is most closely related to Aramaic and Hebrew. Semitic languages are based on a consonantal root system. Every word in Arabic is derived from one or dissimilar root word [1]. By the 7th Century A.D., Arabic started to spread to the Middle East as many people started to convert to Islam. During this time of religious conversions, Arabic substitute many South Arabian languages, most of which are no longer commonly [2] spoken or understood languages. There are three forms of Arabic; Qur’anical Arabic, Modern Standard Arabic, and Colloquial Arabic. Qur’anical Arabic is not used in conversation or in non-religious writing and Modern Standard Arabic is the official language of the Arabic world. Colloquial Arabic refers to Arabic that is spoken with a dialect [3].

The modern Arabic language writing system runs from right to left and is a cursive script [4]. There are twenty eight letters in the alphabet, but because the script of the alphabet is cursive, 22 of the letters take different shapes when they are in initial, medial, final, or isolated positions [5]. There are six letters in the alphabet which have only two presumable forms because you only connect to them; they cannot be connected from. The three long vowels are represented within the alphabet. However, the three short vowels are not. Short vowels can be indicated by optional diacritical markings [6], but these are most often not written. Those texts in which they are written are usually of a religious nature and they are included to ensure that the proper pronunciation is made for all the words. Note that Arabic is particularly rich in uvular, pharyngeal, and pharyngealized ("emphatic") sounds.

The Arabic handwritten script recognition is an open field of research which has a large amount of scope for development. A some models are already enforcing for the hand written character recognition system include framework based models, support vector machines, stochastic models, and learning-based models etc. In this paper using a Hidden Markov Models because Hidden

Markov Models are mainly sequence [7] classifiers and are frequently used for recognition of Arabic handwritten script. They are stochastic models and can encounter with noise and also give diversifications in Arabic handwriting. A progressist viewpoint has been proposed to reform simplified fuzzy ARTMAP Neural Network [8] performance for character recognition of handwritten Arabic script. The few fuzzy values are used for the similar Arabic script to ameliorate recognition. The fuzzy

ARTMAP beforehand gives preferable execution for other characters [9]. In this paper available the all information keeps together by both labeled and unlabeled Arabic patterns, it is essential to intermingle supervised and unsupervised learning in a single training algorithm. We are using a simplified fuzzy ARTMAP and hidden Markov models in Arabic script. We have acquired spanking outcome.

II. THE HIDDEN MARKOV MODELS

The Hidden Markov Model (HMM) is a sinewy statistical tool for modeling productive sequences that can be characterized by an underlying process productive a noticeable sequence [10]. In today's scenario hidden Markov model have found application in many areas take an interest in signal processing, handwriting recognition, phrase chunking, and character recognition and in particular speech processing. Andrei Markov gave his name to the mathematical theory of Markov processes in the early twentieth century, but it was Baum and his colleagues that developed the theory of hidden markov model in the 1960s [11].

In a hidden Markov model, one does not know anything about what originates the observation sequence. The number of states, the transition prospect, and from which state an observation is originated are all unknown [12]. Instead of intermingling each state with a cogent output; each state of the hidden Markov model is associated with a prospect function. At time t, an observation o_t is originate by a prospect function b_j (o_t), which is associated with state j, with the likelihood,

$$b_j(o_t) = P(o_t|X_t = j)$$

An HMM is composed of a five tuple: (S, K, ∏, A, B)

1. S = {1……..N} is the set of states. The state at time t is denoted s_t.

2. K = {k_1…….k_M} is the output alphabet. In a discrete observation density case, M is the number of observation pick. In the above example, M equals the number of presumable movements.

3. Initial state delivery ∏ = {π_i}, i ϵ S. π_i is defined as:

$$\pi_i = P(s_1 = i)$$

4. State transition prospect delivery A = {a_{ij}}, i, j, ϵ S.

$$a_{ij} = P(s_{t+1}|s_t), 1 \leq i, j \leq N$$

5. Observation symbol prospect delivery B = bj (o_t). The prospect function for each state j is:

$$b_j(o_t) = P(o_t|s_t = j)$$

Since modeling a problem as a hidden Markov model, and acknowledging that some set of data was originated by the hidden Markov model, we are potentially viable to calculate the prospect of the observation sequence [13] and the potential fundamental state sequences. We can train the model parameters based on the comply data and get a more actual model. Then use the trained model to predict unappreciated data.

A Hidden Markov Model is that the states are look on directly on the Markov Model, and look on indirectly with unpredictability in the hidden markov model. The above is best be an example using the graphical model representation see in Fig. 1.

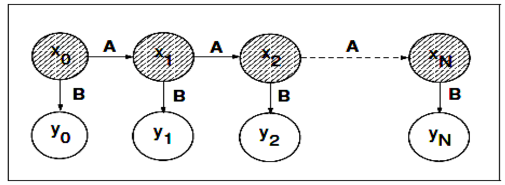

Fig. 1. The Graphical model of a Hidden Markov Model

In the Markov Model we could write out the thorough likelihood, since all the variables have been look on. In describing the likelihood [14] of the Hidden Markov Model, we have to dislodge all unpredictability on the hidden states X, which is done by conjecture. To calculate the likelihood of the set of observations D = {y1, y2, y3,……y_N} using the above rules gives:

$$p(D) = \sum_{x_1, x_2, .., x_N} p(x_1)p(y_1|x_1) \prod_{n=2}^{N} p(x_n|x_{n-1})p(y_n|x_n)$$

The aloft expression can also be written using the annotation of transition matrix, observation matrix and initial state likelihood:

$$p(D) = \sum_{x_1, x_2, .., x_N} \pi_{x_1}(1) b_{x_1}(y_1) \prod_{n=2}^{N} a_{x_{n-1}, x_n} b_{x_n}(y_n)$$

Where bx_n = S_j (yn =c_i) = $b_{j,i}$ is the emission likelihood (the likelihood of emitting symbol c_i have given we are in state S_j). The usual hidden markov model outlook framework is an unsupervised learning technique which assent new patterns to be found. It can handle variable lengths of input sequences, without having to inflict a template to cognize.

III. THE PROBLEM STATEMENT

The Arabic character recognition is exceedingly arduous to automate. The humankind being can diagnosticate variegated objects and make cognition out of volumetric amount of visual information, seemingly requiring very diminutive attempt. The emulate task execution by humankind to diagnosticate to the extent allowed by physical barricades will be extremely gainful for the system. The difficulty contains in the real world data handwritten Arabic alphabets, where handwritten Arabic characters are the input to the system, while in print characters will be goal output of the system.

In this paper collection of Arabic character data. We are particular piece of paper has to be designed for the Arabic data collection. The Arabic data are collected from many people from various ages and realm. The Arabic character data obtaining is done manually i.e., The bond piece of paper was provided to the respondent and asked to inscribe the Arabic characters from to for one time. Because bond paper is a strong, high quality, durable writing paper similar to bank paper, but having a weight greater than 50 g/m^2. After that bond piece of paper are scanned using HP Scanjet 5590 Digital Flatbed Scanner at 2400 dpi optical resolution, which gives low noise and good quality image. The digitized images are stored in BMP file shown in Fig. 2.

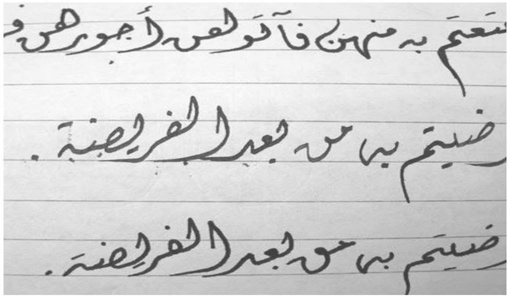

Fig. 2. The Handwritten Arabic Script Data Collection

IV. PRAPOSED SOLUTION BY SIMPLIFIED FUZZY ARTMAP FOR ARABIC SCRIPT

The ART was introduced by Stephen Grossberg in 1976.The term resonance refers to the so called resonant state of network in which a category [15] prototype vector matches the current input vector so close enough that the orienting system will not generate a reset signal in the other consideration layer. The networks learn only in their resonant states [16]. The architecture of ART is based on the idea of adaptive resonant feedback between two layers of nodes as developed by Grossberg (1988).

ART permitted for cluster input by unsupervised learning. One can current input patterns [17] in any order. Each time when a pattern is presented, a suitable cluster unit is selected and the cluster's weights are adjusted to let the cluster unit to cognize the pattern. There is one drawback with HMM also that is it takes lots of training time in particular at a higher number of states the Arabic characters. Also the recognition time is elongate as the increase in states. Many researchers thought that Backpropagation as a solution for the Pattern recognition. But the Fuzzy ARTMAP based on Predictive ART (ARTMAP) can also be used for pattern recognition of characters. This network gives optimum performance on image the Arabic character recognition [18].

Therefore, in this paper, we are applied to Arabic character recognition too. The network will be more accomplished for the recognition of similar characters. ARTMAP is supervised, self learning, real time, a self organizing network, which supports slow and fast Arabic characters learning, whereas, Backpropagation is a supervised and supports slow learning. This model employs simple learning equations with a single Arabic user selectable parameter and can learn single training pattern within a small number of training iterations. The Fuzzy ARTMAP efficient, high speed, accuracy in both of Arabic character recognition like online as well as offline [19]. It has a number of parameters and it requires no problem conspicuous crafting or liking of initial weights or parameters.

Simplified Fuzzy ARTMAP is the structure developed by Kasuba in the year 1993. It is a vast simplification of Carpenter and Grossberg's fuzzy ARTMAP [20]. This has a diminished computational overhead and architectural exorbitance when compared to its predecessor fuzzy ARTMAP. The fuzzy ARTMAP neural network architecture is competent of self-organizing stable recognition categories in response to pleasing one's own mind sequences of analog or binary input patterns. It endows a unique solution to the stability-plasticity suspense faced by autonomous learning systems. Because fuzzy ARTMAP can perform fast, stable, on-line, unsupervised or supervised, incremental learning, it can learn from novel events encountered in the field, yet overcome the problem of catastrophic forgetting associated with many renowned neural network classifiers [21].

FAM is composed of a pair of fuzzy ART modules, ART_a and ARTb connected by an inter-ART module called Mapfield. ART_a and ART_b are used for coding the input and output patterns serially, and Mapfield allows mapping between inputs and outputs. The ART_a modules [22] include the input layer F^a_1 and the competitive layer F^b_2. A preprocessing layer F^a_0 is also added before. Analogous layers appear in ART_b. Fuzzy ARTmap architecture is shown in Fig. 3.

The preparative input vectors have the form: $a = (a_1, \ldots, a_n) \in \{0, 1\}^n$. A data preprocessing technique called complement coding is featured in the two fuzzy art modules by the F^a_0 (and F^b_0 serially) layer in order to avoid diffusion of nodes. Each input vector a produces the normalized vector $A = (a, 1 - a)$ whose L1 norm is constant: $|A| = n$.

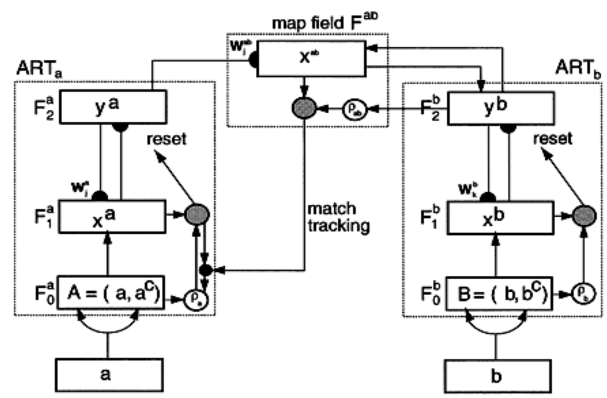

Fig. 3. The Fuzzy ARTMAP Architecture

Let M_a be the number of nodes in F^a_1 and N_a be the number of nodes in F^b_2. Due to the preprocessing step, $M_a = 2n$. W^a is the weight vector between F^a_1 and W^{ab}_j . Each F^a_2node represents a class of inputs grouped together, notify as a category. Each F^a_2category has its own set of adaptive weights stored in the form of a vector W^a_j, $j= 1\ldots\ldots N_a$ whose geometrical interpretation is a hyper-rectangle inside the unit box. Similar notations and affirmations are valid for ART_b that receives the m-dimensional input vectors. For a classification problem, the class index is the same as the category number in F^b_2, thus ART_b can be simply substituted an N_b dimensional vector.

The Mapfield module allows fuzzy ARTmap for execution of heteroassociative tasks, establishing many-to-one links between various categories from ART_a and ART_b, serially. The number of nodes in Mapfield is equal to the number of nodes in F^b_2. Each node j from F^a_2 is linked to every node from F^b_2via a weight vector W^{ab}_j. The learning algorithm is sketched below. Training pattern, the watchfulness parameter factor is set equal to its baseline value, and all nodes are not inhibited. For each input A, a fuzzy choice function is used to get the response for each F^b_2 category:

$$T_j(A) = \frac{|A \wedge w_j^a|}{\alpha_a + w_j^a}, \ j = 1, \ldots\ldots, N_a \qquad \textbf{(1)}$$

Let J be the node with the highest value computed as in (1). If the resonance condition from eq. 2 is not fulfilled,

Then the J_{th} node prevents such that it will not take part to further competitions for this pattern and a new search for a resonant category is performed. This might lead to the creation of a new category in ART_a.

$$\rho(A, w_j^a) = \frac{|A \wedge w_j^a|}{|\mathrm{A}|} \geq \rho_a \qquad (2)$$

An identical process occurs in ART_b and let K be the winning node from ART_b. The F^b_2output vector is set to:

$$y_k^b = \begin{cases} 1, & if \quad k = K \\ 0, & otherwisw \end{cases} \quad \mathbf{k= 1,\ldots., } N_b \quad (3)$$

An output vector X^{ab} is formed in Mapfield: $X^{ab} = y^b \wedge W^{ab}_j$. A Mapfield vigilantly test controls the match between the predicted vector X^{ab} and the target vector y^b :

$$\frac{|X^{ab}|}{|y^b|} \geq \rho_{ab} \qquad (4)$$

Where $\rho_{ab} \in \{0, 1\}$ is a Mapfield vigilantly parameter. If the test from (4) is not passed, then a sequence of steps called match tracking is initiated (the vigilantly parameter ρ a is increased and a new resonant category will be solicited for ART_a), otherwise learning occurs in ART_a, ARTb and Mapfield:

$$w_j^{a(new)} = \beta_a(A \wedge w_j^{a(old)}) + (1-\beta_a)w_j^{a(old)} \qquad (5)$$

(And the analogous in ART_b) and $W^{ab}_{jk} = \delta_{kk}$, where δ_{ij} is Kronecker's delta. With respect to β_a, there are two learning modes firstly the speedy learning for $\beta_a = 1$ for the entire training process, and secondly the speedy commit and gently recode learning corresponds to setting $\beta_a = 1$ when creating a new node and $\beta_a < 1$ for subsequent learning.

In batch supervised learning mode, fuzzy ARTMAP may also be accomplished in that its asymptotic [23] generalization error can be attained for a moderate time and space complexity. They have been swimmingly applied in complex real-world pattern recognition tasks such as the recognition of radar signals multi-sensor image fusion [24], remote sensing and data mining recognition of handwritten characters and signature verification .

V. WORKING OF FEATURE EXTRACTOR FOR ARABIC SCRIPT

The assortment of two-dimensional objects from Arabic visual image data is vital Arabic pattern recognition task. The feature is defined as a function of one or more measurements, each of which determine some quantifiable property of an Arabic object, and is computed such that it quantifies some valued Arabic characteristics of the object. We classify the various features [24] currently employed as follows:

• *General features:* Application unattached features such as color, texture, and shape. According to the abstraction level, they can be further divided into three types, firstly the pixel level features these features calculated at each pixel, e.g., color, location. Secondly the local features these features calculated over the results of subdivision of the image band on image segmentation or edge detection. Lastly the global features: these features calculated over the overall image or just a regular sub - area of an image.

• *Domain-specific features:* Application unattached features such as human faces, fingerprints, and conceptual features. These features are frequently a synthesis of low-level features for a specific domain. On the other hand, all features can be coarsely classified into low-level features and high-level features. Low-level features can be extracted directed from the actual images, whereas high-level feature extraction must be based on low level features [25].

This task is an example many facets of a typical Arabian pattern recognition problem, including feature selection, dimensionally deficiency and the use of prestigious descriptors jiffy are the extracted features derived from raw measurements. Where jiffy are used to obtain Arabic script Scaling (ASS), Arabic script Rotation (ASR), Arabic script Translation (AST) unalterable. The disposition of immutability to ASS, ASR, AST transforms may be derived using the function of jiffy. The jiffy transformation of an Arabic image function ĄĪF(x,y) is given by:

$$\mathrm{lmn} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^m y^n \,\text{ĄĪF}(x,y)\, dx\, dy \quad \mathrm{m, n} = 0,1,2,\ldots\ldots,\infty$$

In the case of a spatially calumniate 9×11 (M×N) character denoted by ĄĪF(i,j)is approximated as,

$$\mathrm{lmn} = \sum_{i=0}^{5}\sum_{j=0}^{7} i^m j^n \,\text{ĄĪF}(i,j)$$

Now the value of ĄĪF(i,j)0 or 1 keep faith upon whether the $(i,j)^{th}$ pixel The moment severity is represented by several prospects like the way of handwriting, ink used for Arabic written character i.e. 0 ≤ ĄĪF(i,j)≤ 1 point to that the severity [26] falsehood amid the ends of a spectrum. However ĄĪF(i,j) is static over any pixel realm and ponder it as pivotal jiffy.

The pivotal jiffy is given by:

$$\mu_{mn} = \sum_{i=0}^{5}\sum_{j=0}^{7} (i - \hat{i})^m (j - \hat{j})^n \,\text{ĄĪF}(i,j) \quad \text{Where}$$

$$\hat{i} = \frac{l10}{l00}, \quad \hat{j} = \frac{l01}{l00}$$

The pivotal jiffies are so far sentient to ASR and ASS transformation. The scaling unalterable may be procured by ahead normalizing μ_{mn} as:

$$\eta mn = \frac{\mu mn}{\mu 00^{\frac{m+n}{2}+1}} \qquad m+n=2,3,\ldots..$$

VI. THE ALGORITHEM FOR TRANING AND INFERENCE PHASES FOR ARABIC SCRIPT

The algorithms for Training and Inference phases of SFARTMAP on the basis of the prolonged definition of complementary distribution are as follows:

A) The Training phase of Arabic Script

Phase 1: Select a suitable value for the vigilantly parameter ($0 < þ < 1$) and a small value for š. The conglomeration number of training epochs to the desired number of training epochs and Enumerate of training epochs to 0.

Phase 2: $x \leftarrow 1$;
Enumerate of training epochs = Enumerate of training epochs +1; While (Enumerate of training epochs ≤ number of training epochs)
Repeat Phases 3 – 12 else 13;

Phase 3: Input the pattern vector $I_x = (b_{x1}, b_{x2}, b_{x3}, b_{x4},……., b_{xd})$ of dimension d and its ranking R_x. [28]

Phase 4: Count the augmented input vector using the detailed definition of complementation of Fuzzy set under the presumable cases.
$BI_x = (b_{x1}, b_{x2}, b_{x3}, b_{x4},……., b_{xd}, 1- b_{x1}, 1- b_{x2}, 1- b_{x3}, 1- b_{xd})$

Phase 5: If BI_x is the first input in the given ranking Rx conglomeration the top down weight vector W_x as BI_x Link Wx to the ranking R_x.
Go to Phase 12 else 13.

Phase 6: If BI_x is an input pattern vector whose ranking previously exits, then count the conative function $CF_y(BI_x)$ for each of the existing top-down weight nodes TDW_y

$$CF_y\left(BI_x\right) = \frac{BI_x \wedge W_x}{\check{s} + W_y}$$

Phase 7: Select that top-down weight node N which records the transcendent [29] conative function $N_c(BI_x) = max_y$ $Ny(BI_x)$

Phase 8: Count the correspond function $CF_n(BI_x)$ of the vanquish node N; If $CF_n (BI_x) > þ$ and R_x is same as that ranking R_N linked to W_N Then update weight vector W_N as $W_N^{recently} = W_N^{longstanding} + (I \wedge W_N^{longstanding})$

Phase 9: If $CF_n (BI_x) > þ$ and R_x is not the ranking R_N linked to W_N then Initiate harmonize tracing by setting to $CF_n (BI_x)$ and incrementing by a miniature value ƛ then
$þ = CF_n (BI_x) + ƛ$
If few much top down weight nodes exist then contemplate the next topmost winner W_N among the top-down weight nodes
Go to Phase 8;
Else go to Phase 11;

Phase 10: If $CF_n (BI_x) < þ$ then If few much top down weight nodes exist, then Contemplate the next topmost winner W_N among the top-down weight nodes.
Go to Phase 8;
Else go to Phase 11;

Phase 11: Make a recently top-down weight node RW_{first} such that $W_{first}= BI_x$ and link the node to the ranking R_N;

Phase 12: If nope, more input patterns, then go to Phase 14;

Phase 13: Otherwise $x \leftarrow x +1$
Go to Phase 3;

Phase 14: GOTO Phase 2;

B) The Inference phase of Arabic Script

Phase 1: Let W_y , y=1,2,3,………..,m allude m top-down weight vectors procured after training the network with a given set of training patterns;

Let I_x be the conjecture pattern set each of whose ranking is to be drawn conclusion of the network;
$x \leftarrow 1$;

Phase 2: Perceive input I_x;

Phase 3: Count the augmented input BI_x;

Phase 4: for $y \leftarrow 1$ to m count the conative functions

$$CF_y\left(BI_x\right) = \frac{BI_x \wedge W_x}{\check{s} + W_y}$$

Phase 5: Select the winner N among the M conative functions $N_c(BI_x) = max_y\ Ny(BI_x)$

Phase 6: Output ranking R_N linked to $N_c(BI_x)$ as the one to which I_x pertain to.

Phase 7: If nope, more conjecture pattern vectors
Then exit
Else $x \leftarrow x +1$;
Go to Phase 2.

VII. EXPRIMENTAL RESULTS

The performance of the Simplified Fuzzy ARTMAP and Hidden Markov Models (HMM) is given in figure 4. We look on that up to noise level of 0.20 to 0.25 and handwritten recognition of Arabic Script is 100%. The table 1 shows the feature value of handwritten Arabic characters. In the next table 2 gives a recognition rate, which is based on the disparity between feature values of ideal and handwritten Arabic characters. In table 2 the last row notifies the average of handwritten Arabic character recognition rate. We look on that up to 96.38% recognition is instate for handwritten Arabic Script.

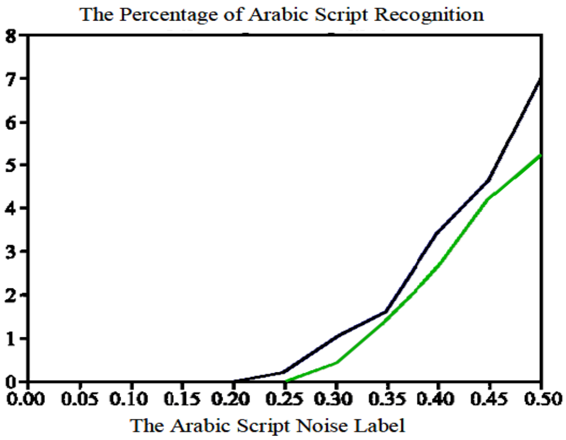

Fig. 4. The Performance of Simplified Fuzzy ARTMAP and Hidden Markov Models (HMM)

Table 1: The Handwritten Arabic Character of Feature Value

د	خ	ح	ج	ث	ت	ب	أ
92	74	96	42	57	64	91	84
89	61	84	29	67	39	83	68
73	58	69	71	26	47	51	73
57	69	58	67	78	89	78	44
78	44	73	39	54	71	69	57

Table 2: The Handwritten Arabic Character of Recognition Rate

د	خ	ح	ج	ث	ت	ب	أ
92.00	84.00	96.00	72.21	87.55	84.00	91.00	87.00
69.41	81.78	84.00	89.00	77.00	79.00	83.71	93.90
73.87	68.19	79.67	71.62	66.45	87.31	79.00	86.00
87.00	79.37	68.56	87.71	78.00	89.00	88.00	91.11
98.32	95.35	98.26	96.00	90.65	95.00	97.68	99.79

VIII. CONCLUSION

In this paper, we proposed an improved on recognition of handwritten characters of Arabic script. Arabic is now the 6th most spoken language in the world and is spoken by more than 200 million people worldwide. The Arabic script handwriting recognition is a very challenging task due to its cursive nature. Because every Arabic handwritten character has unlimited shapes, patterns and styles even when it is written by the same or a different Arabic person. The most Arabic character recognition systems can not read offended documents and handwritten Arabic script or character. In this study, we are putting forward an Arabic handwritten character recognition system using Simplified Fuzzy ARTMAP. The results of simulations Arabic script database illustrate that a precipitant, accurate and noise obstructive module has been successfully designed by using Simplified Fuzzy ARTMAP of the mentioned methods. An experimental result has shown 96.38% recognition rate that the Simplified Fuzzy ARTMAP is patently preferable to the other model in recognizing the handwritten Arabic script.

REFERENCES

[1]. Versteegh, Kees. 1997a. The Arabic Language. New York: Columbia University Press.

[2]. Suleiman, Yasir, ed. 1994. Nationalism and the Arabic Language: A Historical Overview, pages 3–24. Surrey: Curzon Press Ltd.

[3]. Belnap, R. Kirk and Niloofar Haeri. Structuralist Studies in Arabic Linguistics: Charles A. Fergusonís Papers, 1954-1994. Leiden: Brill, 1997.

[4]. MA. Attia , T. Salakoski , F. Ginter , S. T. Pyysalo ,Accommodating Multiword Expressions in an Arabic LFG Grammar , In Finland Springer-Verlag Berlin Heidelberg, vol 4139, pp 87 – 98, 2006

[5]. Farghaly, Ali. December 2008. Arabic NLP: Overview, state of the art, challenges and opportunities. In The International Arab Conference on Information Technology, ACIT2008 . Hammamat, Tunisia.

[6]. J. Dichy ,On lemmatization in Arabic. A formal definition of the Arabic entries of multilingual lexical databases, ACL 39th Annual Meeting. Workshop on Arabic Language Processing; Status and Prospect. Toulouse, pp 23-30, 2001.

[7]. L. R. Rabiner and B. H. Juang. An introduction to hidden Markov models. IEEE ASSP Mag., Vol.3, No.1, p.4-16, June 1986.

[8]. M. Taghi, V. Baghmisheh, and P. Nikola. A Fast Simplified Fuzzy ARTMAP Network. Neural Processing Letters, 17, 2003, 273–316.

[9]. G. A. Carpenter, S. Grossberg, and D. B. Rosen, “Fuzzy ART: fast stable learning and categorization of analog patterns by an adaptive resonance system,” Neural Networks, 4:6, 759-771, 1991.

[10]. E. Fosler-Lussier : Markov Models and Hidden Markov Models : A Brief Tutorial, Technical Report (TR-98-041), December 1998, International Computer Science Institute, Berkeley, California.

[11]. X. D. Huang, Y. Ariki, and M. A. Jack. Hidden Markov Models for Speech Recognition. Edinburgh University Press, Edinburgh, 1990.

[12]. S. Fine, Y. Singer, and N. Tishby. The hierarchical Hidden Markov Model: analysis and applications. Machine Learning, 32, 1998.

[13]. R. Nag, K. H. Wong, and F. Fallside. Script recognition using hidden markov models. In ICASSP 86, 1986.

[14]. T. Jebara and A. Pentland. Maximum conditional likelihood via bound maximization and the CEM algo- rithm. In Advances in Neural Information Processing Systems vol 11, pp 494 – 500, MIT Press, 1998

[15]. G. A. Carpenter, S. Grossberg, N. Markuzon, J. H. Reynolds, and D. B. Rosen, “Fuzzy ARTMAP: a neural network architecture for incremental supervised learning of analog multidimensional maps,” IEEE Trans. on Neural Networks, 3:5, 698-713, 1992.

[16]. E. Granger, et. al. “Classification of incomplete data using the fuzzy ARTMAP neural network,” Proc. 2000 Int. Joint Conference on Neural Networks, 4, 2000, pp. 35-40.

[17]. R. Andonie and L. Sasu. Fuzzy ARTMAP with input relevances. IEEE Transactions on Neural Networks, 17, 2006, 929–941.

[18]. Kwan, H. K., and Cai, Y. (1994). ‘‘A fuzzy neural network and its application to pattern recognition.’’ IEEE Trans. on Fuzzy Systems, 2(3), 185–191.

[19]. C. P. Lim, H. H. Toh, and T. S. Lee, ”An evaluation of the fuzzy ARTMAP neural network using offline and on-line strategies,” Neural Network World, 4, 327-339, 1999.

[20]. I. Dagher, M. Georgiopoulos, G. L. Heileman, and G. Bebis. Fuzzy ARTVar: An improved fuzzy ARTMAP algorithm.In Proceedings IEEE World Congress Computational Intelligence, Anchorage, 1998, 1688–1693.

[21]. Vazquez-Lopez, J. A., Lopez-Juarez, I., Peña-Cabrera, M. 2010. On the use of the FuzzyARTMAP Neural Network for Pattern Recognition in Statistical Process Control using a Factorial Design. Int. J. of Computers, Communications & Control, Vol. V (2), pp. 205-215.

[22]. P. Henniges, E. Granger, and R. Sabourin, “Factors of overtraining with fuzzy ARTMAP neural networks,” Int. Joint Conference on Neural Networks, Montreal, Canada, 2005, pp. 1075-1080.

[23]. B. Lerner and B. Vigdor, ”An empirical study of fuzzy ARTMAP applied to cytogenetics,” IEEE Convention of Electrical and Electronics Engineers in Israel, 2004, pp. 301-304.

[24]. M. Taghi, V. Baghmisheh, and P. Nikola. A Fast Simplified Fuzzy ARTMAP Network. Neural Processing Letters, 17, 2003, 273–316.

[25]. Addison, J F D, Wermter, S and MacIntyre, J. 1999 Effectiveness of feature extraction in neural network architectures for novelty detection, ICANN-99, Ninth International Conference on Artificial Neural Networks”, Edinburgh, UK, September 1999, pp976-981.

[26]. Yusuf Perwej , Dr. Ashish Chaturvedi, “Machine Recognition of Hand Written Characters using Neural Networks” for published in the International Journal of Computer Applications (IJCA) ,USA , Vol. 14, No.2, January 2011, Pages 6- 9, ISSN 0975 – 8887, DOI : 10.5120/1819-2380

[27]. E. Saber, A.M. Tekalp, ”Integration of color, edge and texture features for automatic region-based image annotation and retrieval,” Electronic Imaging, 7, pp. 684–700, 1998.

[28]. I. Dagher, M. Georgiopoulos, G. L. Heileman, and G. Bebis. Fuzzy ARTVar: An improved fuzzy ARTMAP algorithm. In Proceedings IEEE World Congress Computational Intelligence WCCI’98,Anchorage, 1998, 1688–1693.

[29]. E. Gomez-Sanchez, Y. A. Dimitriadis, J. M. Cano-Izquierdo, and J. Lopez-Coronado. Π ARTMAP: Use of mutual information for category reduction in fuzzy ARTMAP. IEEE Transactions on Neural Networks, 13, 2002, 58–69.

Dr. Yusuf Perwej Assistant Professor in the Department of Computer Science & Engineering Al Baha University, Al Baha , Kingdom of Saudi Arabia (KSA). He has authored a number of different journal and paper. His research interests include Soft Computing, Artificial Neural Network, Machine Learning, Pattern Matching, Pattern Recognition, Artificial Intelligence, Image Processing, Fuzzy Logic, Genetic Algorithm, Robotics, Bluetooth and Network etc. He is a member of IEEE.

Dr. Shaikh Abdul Hannan Assistant Professor in the Department of Computer Science & Engineering Al Baha University, Al Baha , Kingdom of Saudi Arabia (KSA). He has authored a number of different journal and paper. His research interests include Data Mining and Data Warehouse, Artificial Neural Network, Artificial Intelligence, Image Processing etc.

Nikhat Akhtar Assistant Professor in the Department of Computer Science & Engineering Integral University, Lucknow, India. She has authored a number of different journal and paper. Her research interests include Soft Computing, Swarm Intelligence, Storage Technology, Artificial Neural Network, Cryptography, Pattern Matching, Pattern Recognition, Artificial Intelligence, Network Security, Fuzzy Logic, Network and Database. She is a member of IEEE.