A FUZZY RECOGNITION MODEL FOR ARABIC HANDWRITTEN ALPHABET

By:
Assistant Lecturer;
Sami Kadhim Hasan Ar-Ramahi
Electronic & communications Department,
College of Engineering,
Nahrain University,
Baghdad- IRAQ.

ABSTRACT

A fuzzy recognition model for some handwritten Arabic alphabet is designed. This fuzzy model could be envisaged as an algorithm which is structured over two concepts. First; the handwritten character variation is modeled by the fuzziness of the feature vector's elements. Second; the notion of entropy is fuzzily modified to extract the amount of information in the elements within the feature vector so as to speed up the recognition process. Consequently, a fuzzy recognition graph of the optimum paths decision tree is designed for the handwritten Arabic alphabet character's recognition.

الخلاصة

تم تصميم منظومة تمييز مضببة لبعض الحروف العربية المكتوبة يدويا. بحيث يمكن مكننة هذه المنظومة كخوارزمية للتمييز باستخدام التكنولوجية الرقمية الحديثة. وتمت هيكلة هذه المنظومة على مفهومين اساسيين.

الاول: تمت النمذجة الرياضية للتغاير الجوهري في الحروف المكتوبة يدويا بقيمة الانتساب المضبب لعناصر متجه الخواص الذاتية الماخوذ من كل حرف غير مطبوع.

الثاني: تم تطوير مفهوم الانتروبي بتقنية المجموعات المضببة لمعرفة حجم المعلومات المتوفرة في كل عنصر موجود ضمن متجه الخواص. ويكون مسار التمييز محكوم بالاكثر احتواء للمعلومات نزولا. هذا مما سيعجّل في تمميز الحرف من دون هدر وقت التمييز بالنظر التسلسلي للعنص تلو الاخر.

وثمرة هذا البحث هي شجرة تمييز مضببة ذات اسرع مسارات لتعرف على الحروف العربية غير المطبوعة وبمعدل تمييز يصل الى 100% لمجموعة عينات الحروف التصميمية ، و 95% لمجموعة عينات الحروف الاختبارية.

KEY WORDS

Fuzzy recognitions model, fuzzy entropy, Arabic handwritten pattern recognition

INTRODUCTION

      The task of handwritten characters recognition demands a powerful approach taking into considerations the unpredictable variation in handwritten characters which are unbounded due to the subjective style of each individual. Although some conventional approaches [1] [2] [3] [4] [5] [6] are already developed since 1990, others utilizing the advances within the digital recognition technology to approach the Arabic script pattern recognition [12][13][14][15][16][17][18][19][20][21][27], and some fuzzy approaches are recently reported by Abuhaiba groups [7], [8], however this research utilizes an alternative optimum fuzzy path seeking recognition approach.

      Each character is written inside a square frame with sixteen radial axes drawn from its center, the number of intersections made by any character with the radial axes will be considered as the elements of its feature vector. However, the amount of information per any ray is extracted from the feature's vagueness (fuzziness) by an index of fuzziness, and the maximum information per ray will be the criterion for the design of the decision tree graph.

      An experiment, on some handwritten Arabic alphabet, is conducted. The designing data of 56- characters see fig. (1), are fully recognized.

Fig.(1): The Alphabet characters designing samples are to be recognized by the fuzzy model, e.g. if you see the sample X^5_9 within one of the fuzzy recognition tree graphs then it means sample number 5 from the X_9 entity.

A FUZZY RECOGNITION MODEL:

The handwritten Arabic alphabet recognition technique, in this paper, is a fuzzy entropic recognition approach which can be formally described by the following fuzzy model. Let the handwritten characters be of (n) distinguishable entities;

$$X = \{ x_1^m, x_2^m, x_3^m \ldots x_n^m \} \quad \ldots\ldots\ldots\ldots \text{ (1)}$$

Where; the superscript (m) is the sample's number for each entity (i.e., a handwritten character class). See appendix (1). Practically, this handwritten character, x, can be attributed as a feature vector, y, of sixteen elements. Each one of them is the intersection number with the sixteen radial axes drawn from the center of a square frame on which the character was scripted;

$$Y = \{ y_1^m, y_2^m, y_3^m \ldots y_n^m \} \quad \ldots\ldots\ldots\ldots \text{ (2)}$$

These elements of the feature vector are of no-crossing, single-crossing, double-crossing and triple-crossing feature(s);

$$y_n^m = \{ y_n^m (r); r = 1,2, \ldots 16\} \quad \ldots\ldots\ldots\ldots \text{(3)}$$

Where, r; is the radial axis ray number.

Formally, a fuzzy subset, F, from the feature vector, y, is established to simulate the vagueness of the linguistic expression "that handwritten character is almost the entity x_n";

$$\mu_F (r): y (r) \rightarrow [0, 1] \quad \ldots\ldots\ldots\ldots \text{ (4)}$$

Where $\mu_F (r)$ is the grade of membership value of the rth feature. Subjectively, this grade of membership function is the π- function [9] [11], since it reflects the context suitability. The membership function's independent variable is the crossing point distance from one of the ray ending (the smallest distance). Thus the fuzzy subset, F, is a set of ordered pairs;

$$F = \{ (y_n^m (r), \mu_F (r)) ; r = 1,2, \ldots 16\} \quad \ldots\ldots\ldots\ldots \text{ (5)}$$

Notably, a unity grade of membership value is assigned to the no-crossing feature since it carries the largest amount of vague belonging to which entity.

The compound grade of membership value for a k- crossing feature, here the highest value of k is three, is evaluated as follows:

$$\mu_F (r) = \min [\mu_F (r, 1), \mu_F (r, 2), \ldots \mu_F (r, k)] \quad \ldots\ldots\ldots\ldots \text{(6)}$$

That is because the amount of information revealed by a certain ray is depending on the elimination of the feature vagueness (fuzziness). Thus an index of fuzziness

which provides a measure of the amount of information in a certain ray may be one of the following fuzzy entropies;

$$D_1(\mu_F(r)) = -\sum_{i=1}^{m} [\mu_F(r, i) \log_e \mu_F(r, i)$$

$$+ \mu_{Fc}(r, i) \log_e \mu_{Fc}(r, i)] \ldots\ldots\ldots (7)$$

$$D_2(\mu_F, P) = -\sum_{i=1}^{m} [\mu_F(r, i) P(r, i) \log_e \mu_F(r, i) P(r, i)$$

$$+\mu_{Fc}(r, i) P(r, i) \log e \, \mu_{Fc}(r, i) P(r, i)] \ldots\ldots\ldots (8)$$

Where;

   m; is the number of the designing handwritten samples.

$\mu_F(r, i)$; is the grade of the membership value in the fuzzy subset, F, for the rth ray's feature from the ith sample.

$\mu_{Fc}(r, i) = 1 - \mu_F(r, i)$.

P(r, i); is the probability of occurrence of a feature in the rth ray in a sample space of the m samples.

Both formulae are an indication for the amount of information per ray so that the index of uncertainty in the first formula is the fuzziness of the feature. While, in equ (8), the randomness as well as the fuzziness of that feature is considered. However, both formulae satisfy some properties [9] [10] [11], such that the amount of information is zero as the fuzzy subset becomes a sharpened subset, that is the membership value is either 0 or near 1.

The ray, r_0, with the largest amount of information is selected as a candidate for the recognition of some handwritten alphabet which is characterized uniquely by only one type of a feature;

$$D(\mu_F(r_0)) = \max_{1 \le r \le 16} [D(\mu_F(r))] \ldots\ldots\ldots (9)$$

We refer to the first formula for simplicity of representation. After selecting, observing, and recognizing, there will be sets of different handwritten alphabet entities, each set is characterized by one type of a feature observed in the selected ray, exclude that ray, separate these common – featured sets, and calculate the amount of information for the remaining rays for each set;

$$D(\mu_F(R)) = -\sum_{i=1}^{M} [\mu_F(R, i) \log_e \mu_F(R, i) + \mu_{Fc}(R, i) \log_e \mu_{Fc}(R, i)] \ldots\ldots (10)$$

Where;

M; is the number of the unrecognized character in a common featured set; $M \le m$

R= 1, 2… r-s

s; is the number of the excluded rays.

Then each set will have a ray with maximum information. It must be observed first;

$$D\left(\mu_F\left(r_1\right)\right) = \max_{1 \leq r \leq r\text{-}s} \left[D\left(\mu_F\left(R\right)\right)\right] \quad \dots\dots\dots (11)$$
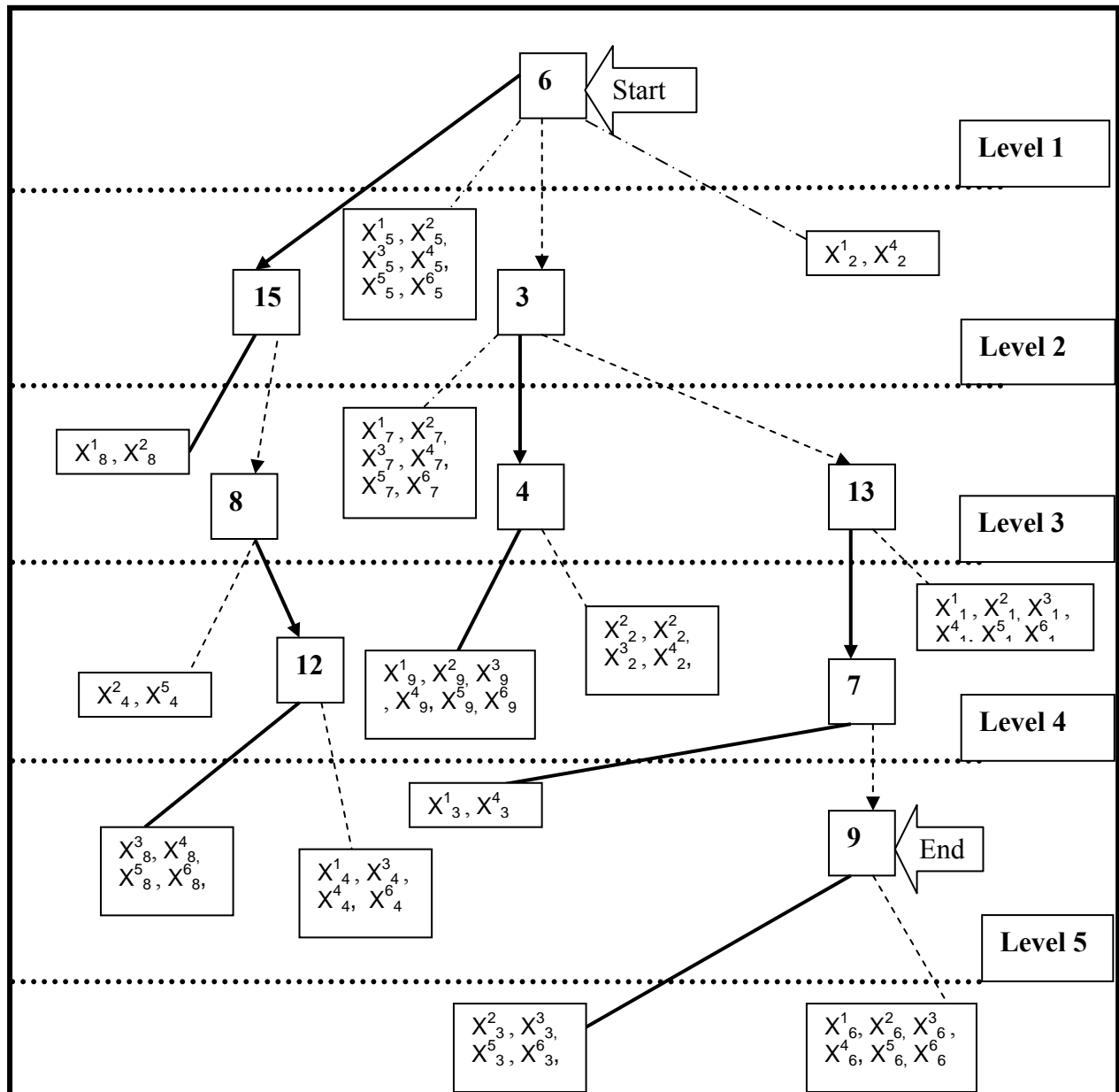
This process of calculating, selecting, observing, excluding, then again calculating will be continued until all of the alphabetic characters in the designing set are recognized. Consequently, a decision tree graph of a hierarchically observed rays so that there are optimum paths of rays observation for the recognition of an unknown handwritten alphabetical characters.

EXPERMENT:

The handwritten alphabet sample was placed on a square frame. The designing sets were 56-samples; six samples for each entity as shown above in fig. (1), and the testing set were 144- samples; twelve samples for each entity.

After measuring the crossing point(s) distance(s) from one of the ray's ending to determine its grade of membership value, we have tabulated the designing set as an entity-ray number matrix, (m x r), where each element is a pair of feature and its membership grade value, as in equ. (5).

Now, the amount of information per ray is revealed by the calculation of the fuzzy entropy by equ. (7) or equ. (8). Therefore, there are two graphs of decision tree as shown below in fig. (2) and fig. (3). Next as an example the decision tree graph of fig (2) will be traced.

6 Start

Level 1

$X^1_5, X^2_5, X^3_5, X^4_5, X^5_5, X^6_5$

X^1_2, X^4_2

15   **3**

Level 2

X^1_8, X^2_8

$X^1_7, X^2_7, X^3_7, X^4_7, X^5_7, X^6_7$

8   **4**   **13**

Level 3

$X^1_1, X^2_1, X^3_1, X^4_1, X^5_1, X^6_1$

X^2_4, X^5_4

12 $X^2_2, X^2_2, X^3_2, X^4_2,$

$X^1_9, X^2_9, X^3_9, X^4_9, X^5_9, X^6_9$

7

Level 4

X^1_3, X^4_3

$X^3_8, X^4_8, X^5_8, X^6_8,$

$X^1_4, X^3_4, X^4_4, X^6_4$

9 End

Level 5

$X^2_3, X^3_3, X^5_3, X^6_3,$

$X^1_6, X^2_6, X^3_6, X^4_6, X^5_6, X^6_6$

LEGEND:

- The doted lines are the intersections number primitives of no-crossing feature as _____, Single-crossing feature as --------, double-crossing feature - · - , triple-crossing feature _ ._ _ _
- Numerals inside the boxes present a ray number.
- At each termination dot the recognized alphabet character(s) are stated as X_n^m , where, m indicates the handwritten sample version number, and n indicates the identity number.

Fig. (2): A Fuzzy Recognition Tree Graph is obtained by utilizing equ (7) as the Fuzzy Entropy.

After calculating the fuzzy entropy, by equ (7), the 6th ray has the maximum scalar value so it must be scanned in the entity-ray number matrix, (56 x 16), for the uniquely characterized entity by only one type of crossing. Accordingly, as shown in fig (2), only two versions of the second entity and the whole of the fifth entity can be recognized from the triple-crossing feature and the double-crossing feature, from that ray, respectively. The remaining design samples are categorized into two common-

feature set, where the no-crossing feature set is of sixteen samples and the single-crossing feature set is of thirty-two samples. After excluding the 6th ray, there will be two entity-ray number matrices of (16 x 15) and (32 x 15). For each one of both calculate the fuzzy entropy, select the ray with the maximum information, and scan it for some uniquely featured alphabet and so on, until all of the designing data have been classified as in fig (2). This decision tree graph is tested by twelve samples for each entity, all of them are recognized except those of the second, third and fourth entities which have some misclassification rate of 95%.
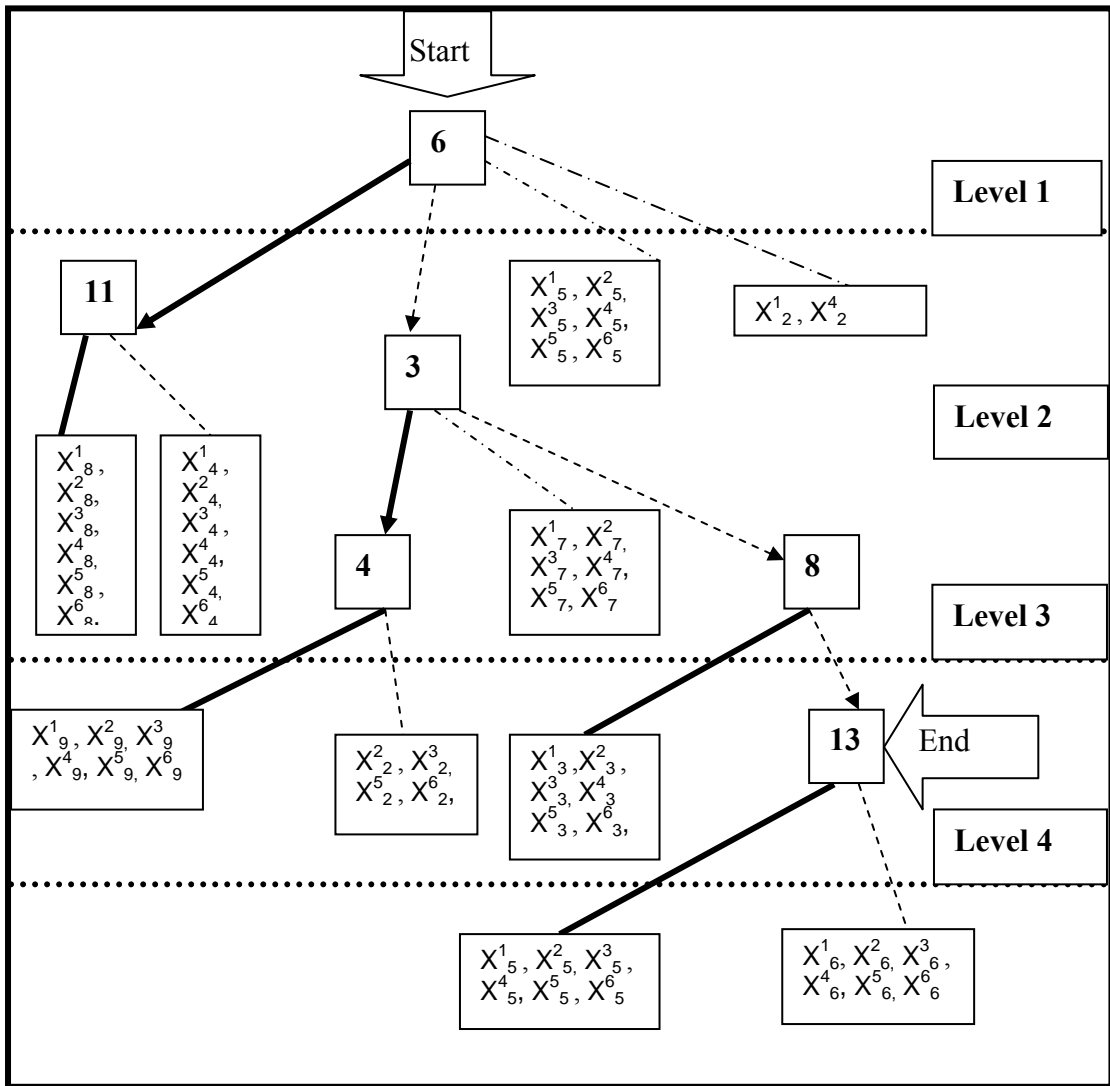
LEGEND:

- The doted lines are the intersections number primitives of No-crossing feature _____, Single-crossing feature --------, Double-crossing feature ‑ ‑ ‑, and Triple-crossing feature _ _ _ _ _ .
- Numerals inside the boxes present a ray number.
- At each termination box the recognized alphabet character(s) are stated as X_n^m , where, m indicates the handwritten sample, and n indicates the identity number.

Fig. (3): A Fuzzy Recognition tree Graph is obtained by utilizing equ (8) as Fuzzy Entropy.

HANDWRITTEN RECOGNITION MODELS COMPARTION

This paper presents an off-line ARABIC alphabet handwritten recognition model of 100% recognition rate for the designed handwritten sample sets and a rec-

ognition rate of 95% for the randomly ARABIC handwritten testing set. This highly success recognition rate is due to that the recognition model is mathematically representing the subjectivity (fuzzy) and the objectivity (probability) of the ARABIC handwritten alphabet.

Margner and El Abed [27][28] compared 14 Arabic handwritten recognition model based on the INF/ENIT- database. Consequently, the higher recognition rate was by the SIEMENS recognition model of (94.58%). The Hidden-Markov Recognizer is the recognition engine utilized by the SIEMENS model. This technique was originally developed in 1993 in which a feature vector is created by a sliding window, then decoded and recognized by a multiple left-to-right models. During the past four decade this model had been in a series of improvements till the above mentioned recognition rate is successfully reached.

Amin [4] designed a handwritten letter recognition model by utilizing a skeleton-base graph representation. The feature vectors were fed into a five-layer neural network which yield a (92%) recognition rate.

Mostafa and Darwish [4] created a baseline-independent algorithm to segment handwritten words into letters and primitives utilizing the chain code representation to successfully achieve a (97.7%) recognition rate.

CONCLUSION

A fuzzy entropy algorithm is designed for the computer recognition of any handwritten Arabic alphabet characters. In the sequel, a decision tree graph can eventually be translated into a fuzzy algorithm consisting of a set of rules in the form; "If … then". So that the ray's feature is observed, and either a handwritten recognized character is obtained or another ray's feature is to be observed.

This fuzzy recognition tree is a computer fuzzy algorithm of significant benefit to be further extended for future Arabic handwritten scripts recognition work of bank checks, mail addresses, forms, and manuscripts [22][23]. Additionally related applications to man-machine communication[27], includes mobile phone screen handwritten script text to be handwritten via a stylus, or a robotic optical character recognition for handwritten messaging, which assist in the automatic processing of handwritten documents / messaging, web-based translation [24], search engines [25], and information retrieval [26].

REFERENCES

* S. Sami El-Dabi, R. Ramsis, and A. Kamel, "Arabic character recognition system: A statistical approach for recognizing cursive typewritten text," Pattern Recognition, vol. 23, pp. 485-495, **1990**.
* R. Haraty and H. El-Zabadani, "Abjad: An Off-line Arabic Handwritten Recognition System," in Proc. International Arab Conference on Information Technology. Doha, Qatar, **2002**.
* K. Mostafa and A. M. D arwish, " Robust base-line independent algorithms for segmentation and reconstruction od Arabic handwritten cursive script ," in proc. IS&T/SPIE Conference, vol. 3651. California, USA:SPIE, pp.73-83. **1999.**
* A. Amin, "Recognition of hand-printed characters based on structural description

and inductive logic programming," Pattern Recognition Letters, vol. 24, pp.
3187-3196, **2003**.

* M. S. Khorsheed, "Recognising handwritten Arabic manuscripts using a single
hidden Markov model," Pattern Recognition Letters, vol. 24, pp. 2235-2242,
2003.

* F. Farooq, V. Govindaraju, and M. Perrone, "Pre-processing Methods for
Handwritten Arabic Documents," in Proc. International Conference on Document
Analysis and Recognition. Seoul, Korea, pp. 267-271. , **2005**.

* I. S. I. Abuhaiba, S. A. Mahmoud, and R. J. Green, "Recognition of handwritten
cursive Arabic characters," Pattern Analysis and Machine Intelligence, IEEE
Transactions on, vol. 16, pp. 664-672, **1994**.

* I. S. I. Abuhaiba, M. J. J. Holt, and S. Datta, "Recognition of Off-Line Cursive
Handwriting," Computer Vision and Image Understanding, vol. 71, pp. 19-38,
1998.

* H. J. Zemmermann, "Practical Applications of Fuzzy Technologies," 1st ed :
Kluwer Academic Publishers, **1999**.

* T. M. Cover and J. A. Thomas, "Elements of Information Theory", 2nd ed :
John Wiley & Sons, Inc., **2006**.

* G. J. Klir , "Uncertainty and Information: Foundations of Generalized
Information theory", 1st ed: John Wiley & Sons, Inc., **2006**.

* S. A. Al-Qahtani and M. S. Khorsheed, "A HTK-Based System to Recognize
Arabic Script," in Proc. 4th IASTED International Conference on Visualization,
Imaging, and Image Processing. Marbella, Spain: ACTA Press, **2004**.

* M. Pechwitz and V. Märgner, "HMM based approach for handwritten Arabic
word recognition using the IFN/ENIT - database," in Proc. International
Conference on Document Analysis and Recognition, pp. 890-894. , **2003**.

* Y. Al-Ohali, M. Cheriet, and C. Suen, "Databases for recognition of handwritten
Arabic cheques," Pattern Recognition, vol. 36, pp. 111-121, **2003**.

* S. Alma'adeed, C. Higgens, and D. Elliman, "Off-line recognition of handwritten
Arabic words using multiple hidden Markov models," Knowledge-Based
Systems, vol.17, pp. 75-79, **2004**.

* R. Haraty and C. Ghaddar, "Arabic Text Recognition," International Arab
Journal of Information Technology, vol. 1, pp. 156-163, **2004**.

* R. Safabakhsh and P. Adibi, "Nastaaligh Handwritten Word Recognition Using a
Continuous-Density Variable-Duration HMM," The Arabian Journal for Science
and Engineering, vol. 30, pp. 95-118, **2005**.

* L. Souici, N. Farah, T. Sari, and M. Sellami, "Rule Based Neural Networks
Construction for Handwritten Arabic City-Names Recognition," in Proc.
Artificial Intelligence: Methodology, Systems, and Applications. Varna, Bulgaria,
pp. 331-340. , **2004.**

* R. El-Hajj, L. Likforman-Sulem, and C. Mokbel, "Arabic Handwriting
Recognition Using Baseline Dependant Features and Hidden Markov Modeling,"
in Proc. International Conference on Document Analysis and Recognition. Seoul,
Korea, pp. 893-897. , **2005.**

* S. M. Touj and N. Ben Amara, "Arabic Handwritten Words Recognition based
on a Planar Hidden Markov Model," International Arab Journal of Information
Technology, vol. 2, **2005.**

* H. Bunke, S. Bengio, and A. Vinciarelli, "Offline recognition of unconstrained
handwritten texts using HMMs and statistical language models," Pattern
Analysis and Machine Intelligence, IEEE Transactions on, vol. 26, pp. 709-720,

   2004.

* M. S. Khorsheed, "Recognising handwritten Arabic manuscripts using a single hidden Markov model," Pattern Recognition Letters, vol. 24, pp. 2235-2242, **2003**.

* S. S. Maddouri, H. Amiri, A. Belaid, and C. Choisy, "Combination of Local and Global Vision Modeling for Arabic Handwritten Words Recognition," in Proc. International Conference on Frontiers in Handwriting Recognition, pp.128 -135., **2002**.

* M. Yaseen, B. Haddad, H. Papageorgiou, S. Piperidis, Mamoun, N. Theo philopoulos, and S. Krauwer, "A Term Base Translator Over the Web," in Proc. ACL/EACL 2001Workshop - ARABIC Language Processing: Status and Pros pects. Toulouse, France, pp. 58-65. , **2001**.

* I. A. Al-Kharashi, "A Web Search Engine for Indexing, Searching and Publish- ing Arabic Bibliographic Databases," in Proc. Internet Global Summit, **1999**.

* I. A. Al-Kharashi and M. W. Evens, "Comparing Words, Stems, and Roots as Index Terms in an Arabic Information Retrieval System," Journal of the American Society for Information Science, vol. 45, pp. 548-560, **1994**.

* H. El Abed, and V. Margner, "Comparison of Different Preprocessing and Feature Extraction Methods for Offline Recognition of Handwritten Arabic Words", 9th International Conference on Document analysis and recognition (icdar2007), Vol.2, pp. 974-978, **2007.**

* V. Margner, and, H. El Abed, "ICDAR Arabic Handwriting Competition",9th International Conference on Document analysis and recognition (icdar2007), Vol.2, pp: 1274 – 1278, **2007** .