Scientific Journal Impact Factor (SJIF): 1.711
International Journal of Modern Trends in Engineering and Research
ISSN (ONLINE) : 2349 - 9745
ISSN (PRINT) : 2393 - 8161

Arabic Handwritten Recognition using Hybrid Transform

Dr. Anmar. A. RAZZAK[1], Mrs. Inaam[2]
[1]*Professor Assistant at the University of AL-Mustansyria/College of Education/Computer Dept. Baghdad/Iraq*
[2]*Postgraduate student at the University of AL-Mustansyria/College of Education/Computer Dept. Baghdad/Iraq*

Abstract—Automatic analysis of handwritten scripts is rapidly becoming an area of intense interest in computer vision and artificial intelligence research communities. In this paper an approach is presented for Arabic handwritten recognition of 58 Arabic characters including the beginning characters, ending characters and some of middle characters. The approach utilizes the hybrid transform in which consists of two transforms; the Wavelet transform and the discrete cosine transform (DCT). The approach suggested includes many steps such as preprocessing, feature extraction and clustering. In feature extraction phase the Wavelet transform and the discrete cosine transform (DCT) were implemented, in the clustering phase the Self Organizing Feature Map (SOFM) produced by Kohonen was implanted. Topological ordering patterns produced by Kohonen Self Organizing Feature Map, in which implemented on feature extracted for each of 58 Arabic characters used. The map will compute the topological relationship between the particular hand written character feature. The method tested using a new comprehensive Database of hand-written Arabic Words, Numbers, and Signatures.

Keywords—DCT, DWT, Arabic character handwritten recognition, SOFM

I. INTRODUCTION

The task of handwriting recognition is the transcription of handwritten data into a digital format. The goal is to process handwritten data electronically with the same or nearly the same accuracy as humans. By doing the processing with computers a large amount of data can be transcript at a high speed. The field of Arabic handwriting characters recognition is divided into the sub-fields of on-line and off-line. In on-line recognition special devices are used to track the movement of the pen and the temporal information is recorded. In off-line recognition an image of the handwritten text is scanned and recorded. The major difference between the two types is that online characters recognition has real time contextual information but offline characters recognition does not .This difference generates a significant divergence in processing architectures and methods.

In general off-line recognition is considered the more difficult task, because of the lack of temporal information. It is possible to construct the image of the handwriting using the information of the movement of the pen; however it is not possible to reconstruct the information of the movement of the pen using only the image. In this thesis the task of off-line handwriting recognition is considered.

Off-line Arabic handwritten character recognition involves numerous challenges owing to the complexity and ambiguity in styles of writing. There are main characteristics for Arabic writing. One of them is that in contrast to Latin text, Arabic is written right to left, rather than left to right. This is perhaps more significant for a human reader rather than a computer, since the computer can simply flip the images. The another characteristic is that different Arabic characters may have exactly the same shapes, and so are distinguished from each other by the addition of complementary characters (the position and number of the associated dots). Hence, any thinning algorithm needs to deal efficiently with these dots without changing the identity of the character. As well as that 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.

There are many studies that interest in characters handwritten recognition can be shown in the survey of studies [1]. From these studies, Asiri and Khorsheed [2], Mowlaei, et al [3], Shanbehzadeh, et al [4], Alaei, et al [5], Hamdi, et al [6], Dehghani, et al [7], Sabri [8]. There are other studies (see [9]) such as MAJIDA ALI ABED HAMID ALI ABED ALASADI 2005[10], Mohammed Z. Khedher, Gheith A. Abandah, and Ahmed M. Al-Khawaldeh2005 [11], Ivan Dervisevic [2006][12], M. Seijas, Ana M. Ruedin[2007][13], Chirag I Patel, Ripal Patel, Palak Patel [2011][14], Sushree Sangita Patnaik and Anup Kumar Panda May 2011[15], Dileep Kumar Patel, Tanmoy Som1, Sushil Kumar Yadav Manoj Kumar Singh [2012][16], Vijay Laxmi Sahu, Babita Kubde (January 2013) [17], Gurpreet Singh Chandan Jyoti Kumar Rajneesh Rani Dr. Renu Dhir (January 2013) [18], Majida Ali Abed, Hamid Ali Abed Alasadi, (August 2013)[19], Argha Roy, Diptam Dutta KAustav, Choudhury (March 2013)[20], Amir Bahador Bayat[2013] [21], Swagatam Das, Arijit Biswas, Sambarta Dasgupta, and Ajith Abraham[22].

The automatic recognition of handwritten characters could be applied in many areas, for example 'form-filling' applications (including handwritten postal addresses, cheques, insurance applications, mail order forms, tax returns, credit card sales slips, custom declarations, and many others)[23].

In this paper we presented approach for offline handwritten recognition of 58 Arabic characters including the beginning characters, ending characters and some of middle characters. We used in this approach the Discrete Wavelet Transform (DWT) and the Discrete Cosines Transform (DCT). The method tested using a comprehensive database [24], which contains set of handwritten Arabic words. We toke from the comprehensive database many words and segmented them manually into characters to be used in our research.

II. PREPROCESSING

The goal of preprocessing is to increase the quality of recognition, precisely this means that the characters are transformed into shapes in which they look like more similar to the class they are belongs to.
The preprocessing involves four main steps, these steps are:

2.1 Segmenting the Words of Database into Characters

The comprehensive database[24] consist of set of Arabic handwritten words, not characters, and 70 significant samples of these words had been chosen and segmented into characters using specified spinning tool, and the segmented characters had been saved.

2.2 Converting the Image into Gray

Another step in the preprocessing is to convert character image type into gray.

2.3 Image Enhancement

After that CVIP tools [25], which are a software package for exploration of Computer Vision and Image Processing, have been used for applying smoothing operation on the character's image using mean filter.

2.4 Image Resize

Image resize is the last step of the preprocessing, in which an image resize operation had been performed on all the images to be of equal size. The new resized image was (20*20) pixel. These equal sized images will be entered into the next phase, the features extraction phase.

III. FEATURES EXTRACTION

Features extraction is considered the most important step in the proposed system, in handwritten scripts the features information are extracted from the characters. These information are assisted in the classification process. In this research, a hybrid transform consist of DWT and DCT have been used to extract the features of the characters. Both DCT and DWT are widely used in the field of digital signal processing applications [26].

3.1 Discrete Wavelet Transform (DWT)

DWT is another technique used to extract the features of the characters. It based on sub-band coding is found to yield fast computation of wavelet transform [27, 28]. The wavelet transforms are used to analyze the signal (image) at different frequencies with different resolutions, to split up the signal into a bunch of signals, representing the same signal, but all corresponding to different frequency bands, and provides what frequency bands exist at what time intervals.
Many wavelet families have been developed with different properties [28]. For 2-D images, applying DWT corresponds to processing the image by 2-D filters in each dimension. This type of wavelets has been used in this research. At each decomposition level, a low-pass filter (LPF) and a high-pass filter (HPF) are applied to each row/column of the image to decompose into one low-frequency sub-band (LL) and three high frequency sub-bands (LH, HL, HH) [29]. Fig. 1 shows decomposition of DWT at one level which is implemented in this research.

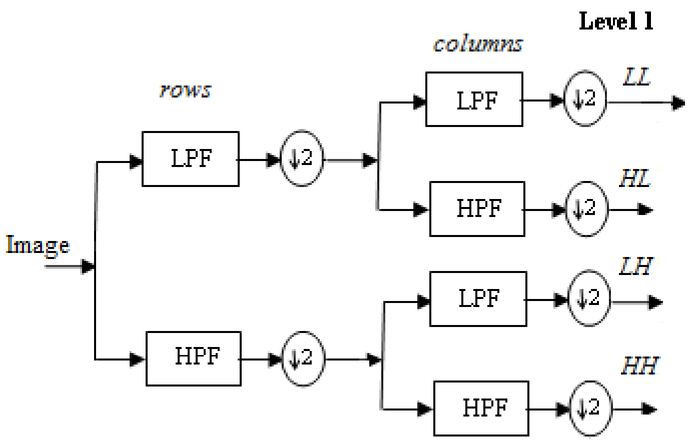

Figure (1) Decomposition of DWT at one level

The LL is known as an approximation of the coefficients and it represents the horizontal and vertical low frequency. The sub-band HL is known as horizontal sub-band, it represents the horizontal high and vertical low frequency. The sub-band LH is known as the vertical sub-band, it represents the horizontal low and vertical high frequency. Finally, the sub-band
HH is known as diagonal coefficients, it represents horizontal and vertical high frequency components. There are many kinds of wavelet transforms which can be applied, such as Haar and Biorthogonal, etc. Each of them has its particular properties. Haar transform had achieved the best result in Arabic handwriting recognition [30, 31]. When the transform is applied, the low frequency coefficients are close to the original image and they contain full details of the image [29, 30]. Therefore, these coefficients are used to detect the features of the character image. Figure (2) describe DWT applying on character image.

(1) *(2)*

Figure (2) DWT decomposition for character image: (1) original image (2) single level decomposition

3.2 Discrete Cosine Transform (DCT)

DCT is a technique that converts image data into its elementary frequency components [26]. It concentrates energy into lower order coefficients. DCT has the ability to convert the energy of the image into a few coefficients [32]. DCT is purely real, DCT expresses a sequence of finitely many data points in terms of a sum of cosine functions oscillating at different frequencies that are necessary to preserve the most important features [27]. DCT clusters high value coefficients in the upper left corner and low value coefficients in the bottom right of the array (m,n). DCT coefficients f (u,v) of f (m,n) are computed by:

$$f(u,v) = a(u)a(v)\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} f(m,n)\cos\left[\frac{(2m+1)\pi u}{2M}\right]\cos\left[\frac{(2n+1)\pi v}{2N}\right]$$

Where

$$a(u) = \begin{cases} \frac{1}{\sqrt{M}}, u = 0 \\ \sqrt{\frac{2}{M}}, 1 \leq u \leq M-1 \end{cases}$$

And

$$a(v) = \begin{cases} \frac{1}{\sqrt{N}}, v = 0 \\ \sqrt{\frac{2}{N}}, 1 \leq v \leq N-1 \end{cases}$$

The higher value DCT coefficients are then extracted in a zigzag fashion and stored in a vector sequence. By applying DCT, an image of a character is represented by this vector. Figure (3) describes the applying of DCT on character image.

(1) *(2)*

Figure (3) applying DCT on character image: (1) original image (2) DCT applying image

IV. CLUSTERING

When solving a pattern recognition problem, the ultimate objective is to design a recognition system which will classify unknown patterns with the lowest possible probability of misrecognition. It is well known that, the complexity of a classifier grows rapidly with the number of dimensions of the pattern space. Thus, the problem is how to face the dimensionality reduction? An efficient way of reducing dimensionality and clustering expression information is to compute the topological relationship between these feature vectors. Thus, Self-Organizing Feature Map (SOFM) neural network is used, the dimensionality is reduced to two dimensions instead of 256. Also the discriminating information regarding the Arabic characters are presented on the Self Organizing Feature map in terms of the topological relationship.

Thus, SOFM are responsible for visualizing low-dimensional views of high dimensional data, having similar character to multidimensional scaling. SOFM learn to recognize groups of similar input vectors in such a way that neurons physically near each other in the neuron layer respond to similar input vectors. One of the most interesting aspects of SOFM is that they learn to classify data without supervision [33]. During the learning the neurons having weight closest with the input vector declare as winner [34]. Based on winning neuron weights of all neighborhood neurons are adjusted by an amount inversely proportional to the Euclidean distance. The learning algorithm is summarized as follows:

1. Initialization: Choose random values for the initial weight vectors $w_{j(0)}$, the weight vector being different for j = 1, 2,...,l where l is the total number of neurons.
   $\mathrm{Wi}=[\mathrm{Wi1}, \mathrm{Wi2}, \dots \dots \dots, \mathrm{Wi}l]^{\mathrm{T}} \in R^n$
2. Sampling: Draw a sample x from the input space with a certain probability.
   $\mathrm{X} = [\mathrm{x1}, \mathrm{x2}, \dots \dots \dots, \mathrm{xl}]^{\mathrm{T}} \in \mathrm{R}^{\mathrm{n}}$
3. Similarity Matching: Find the best matching (winning) neuron i(x) at time t, $0 < t \leq n$ by using the minimum distance Euclidean criterion:
   $i(x) = \arg\min_j \| x(n) - w_j \|$, j= 1,2,….,l
4. Updating: Adjust the synaptic weight vector of all neurons by using the update formula:
   $W j\,(n+1) = Wj\,(n)+\eta(n) h\, j,i(x)\,(n)(X(n)-Wj\,(n))$
   Where η (n) is learning rate parameter, and h**j, ix(**n**)** is the neighborhood function centered around the winning neuron. Both η (n) and are h **j, ix (**n**)** varied dynamically during learning for best results.
5. Continue with step 2 until no noticeable changes in the feature map are observed.

V. EXPERIMENTS AND RESULTS

The experiment is performed throw three main processes (preprocessing, features extraction and clustering) as follows:

1. In the preprocessing many steps are done, these steps include segmenting the words of database into characters, converting the image into gray, image enhancement and images resize with size (20*20).
2. The resulting preprocessed images are used with size (20*20), then DWT transform is applied on the images for one level of decomposition to get four parts (LL , HL ,LH , HH), and the energy part is used only (LL of size (10*10) pixel) .
3. After apply the first transform of the hybrid transform (DWT), then the second transform (DCT) is implemented on the result of (DWT) which is the LL part, the DCT used to compact the energy and to compress the features extracted without losing the features' characteristics.
4. The SOFM is applied to the final features extracted from step 3. The clustering of the features extracted is occurred, such that similar features are grouped together and dissimilar features are grouped into their corresponding clusters. These clusters on the map are distinguished to represent the 58 Arabic handwritten characters (initial, final and some middle characters). The approach

suggested is implemented on 4060 Arabic handwritten characters images taken from the comprehensive database [24].

Because the number of characters is very large, so we showed sample of them, this sample consist of 20 samples for each character. Table (1) shows the number of images taken for each character, and table (2) shows the SOFM parameters used.

Arabic alphabet	Character number	Arabic alphabet	Character number
ء	20	ظ	20
ا	20	عـ	20
أ	20	ـعـ	20
بـ	20	ع	20
ب	20	ـع	20
تـ	20	غـ	20
ت	20	ـغـ	20
ة	20	غ	20
ثـ	20	ـغ	20
ث	20	فـ	20
جـ	20	ف	20
ج	20	قـ	20
حـ	20	ق	20
ح	20	كـ	20
خـ	20	ك	20
خ	20	لـ	20
د	20	ل	20
ذ	20	مـ	20
ر	20	م	20
ز	20	نـ	20
سـ	20	ن	20
س	20	هـ	20
شـ	20	ـهـ	20
ش	20	ه	20
صـ	20	و	20
ص	20	يـ	20
ضـ	20	ي	20
ض	20	ى	20
ط	20	ئـ	20
ظ	20	Total	1160
عـ	20		

Table (1) Number of images for each Arabic handwritten character used

Patterns number	1160
Map size	30*30
Accepted error	0.000009
Iterations number	20000

Table (2) SOFM parameters

The efficiency obtained for these 1160 images for 58 Arabic handwritten characters was 92**%**.

The clustering efficiency using SOFM can be calculated by using the following equation:

$$\frac{\text{no. of character nodes} - \text{no. of non cluster nodes}}{\text{no. of cluster nodes}}$$

Table (3) shows the classification rate for each character and the total rate.

Arabic alphabet	Classification rate	Arabic alphabet	Classification rate
ء	95%	ـعـ	85%
ا	100%	ع	85%
أ	100%	ـع	85%
بـ	100%	غـ	85%
ب	100%	ـغـ	85%
تـ	100%	غ	85%
ت	100%	ـغ	85%
ة	90%	فـ	90%
ثـ	100%	ف	90%
ث	100%	قـ	100%
جـ	95%	ق	85%
ج	95%	كـ	85%
حـ	95%	ك	95%
ح	95%	لـ	95%
خـ	95%	ل	90%
خ	95%	مـ	95%
د	90%	م	85%
ذ	90%	نـ	100%
ر	90%	ن	85%
ز	90%	هـ	90%
سـ	95%	ـهـ	85%
س	95%	ه	100%
شـ	95%	و	100%
ش	95%	يـ	100%
صـ	95%	ي	85%
ص	90%	ى	90%
ضـ	95%	ئـ	90%
ض	90%	Total	92%
ط	90%		
ظ	90%		
عـ	85%		

Table (3) Classification rates for 1160 Arabic handwritten character

Figures (4) show the distribution of the images' features extracted regarding their similarities and dissimilarities grouped as clusters on the map size of 30x30 nodes.
Note: some of characters don't represented because the size of figure here doesn't enough.

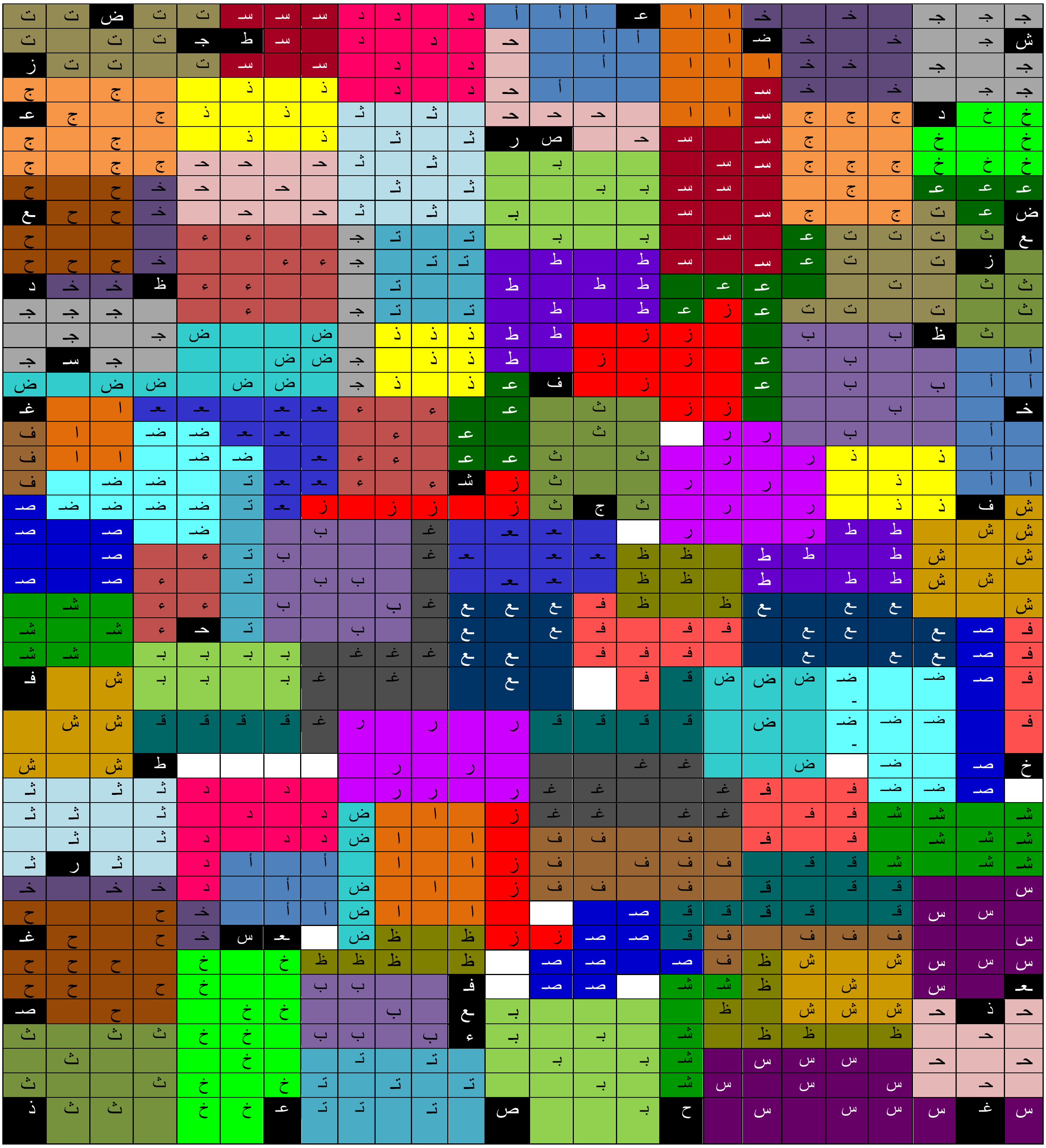

Figure (4) the topological relationships between Arabic handwritten characters images corresponding to their feature coefficient vectors extracted by the hybrid transform and distributed by SOFM.

VI. CONCLUSION

Offline handwritten Arabic character recognition is a difficult problem, because of the great amount of variations in human handwriting. Recognition approaches heavily depend on the nature of the data to be recognized. Since handwritten Arabic characters could be of various shapes and size, the recognition process needs to be much efficient and accurate to recognize the characters written by different users. Also the recognition process depend on the features extraction methods.

Such as when Discrete Cosine Transform DCT had been applied the results obtained were not encouraging. When wavelet transform had been applied also approximately the same results had been obtained. But when we applied the hybrid transform (Discrete Wavelet Transform & Discrete Cosine Transform DCT) the results are distinguishably improved. The results show that the proposed system has a very good accuracy in Arabic character handwritten recognition; the grouping rate achieved was 92% on 580 Arabic handwritten characters.

Different transforms can be combined and implemented for recognition the Arabic handwritten characters. It can be extended for the recognition of words, sentence and documents.
Another research interest will be on the character images degraded or blurred by various reasons. This approach can be used in multilingual character recognition as well.

Some suggestions for future work can be suggested, such as Arabic texts might have short marks, these marks are written as strokes and can affect recognition owing to their location either above or below the characters, like dots. Therefore, these marks need to be recognized and a distinction made between them and the dots.

REFERENCES

[1] Ahmed Lawgali," A Survey on Arabic Character Recognition", University of Benghazi, Benghazi – Libya, International Journal of Signal Processing, Image Processing and Pattern Recognition Vol. 8, No. 2 (2015).
[2] A. Asiri and M. S. Khorsheed, "Automatic Processing of Handwritten Arabic Forms Using Neural Net-works", In Proceedings Of World Academy of Science, Engineering And Technology, (2005), pp. 147–151.
[3] A. Mowlaei, K. Faez and A. T. Haghighat, Feature Extraction with Wavelet Transform for Recognition of Isolated Handwritten Farsi/Arabic Characters and Numerals", In 14th International Conference on Digital Signal Processing, vol. 2, (2002), pp. 923–926.
[4] J. Shanbehzadeh, H. Pezashki and A. Sarrafzadeh, "Features Extraction from Farsi Handwritten Letters", Proceedings of Image and Vision Computing, New Zealand, (2007), pp. 35–40.
[5] A. Alaei, P. Nagabhushan and U. Pal, "Fine Classification of Unconstrained Handwritten Persian/Arabic Numerals by Removing Confusion Amongst Similar Classes", International Conference on Document Analysis and Recognition, (2009), pp. 601–605.
[6] R. Hamdi, F. Bouchareb and M. Bedda, "Handwritten Arabic Character Recognition Based on SVM Classifier", In 3rd International Conference on Information and Communication Technologies: From Theory to Applications, (2008), pp. 1–4.
[7] A. Dehghani, F. Shabini and P. Nava, "Off-Line Recognition of Isolated Persian Handwritten Characters Using Multiple Hidden Markov Models", In Proceedings International Conference on Information Technology: Coding and Computing, (2001), pp. 506–510.
[8] S. Mahmoud, "Recognition of Writer-independent Off-Line Handwritten Arabic (Indian) Numerals Using Hidden Markov Models", Signal Processing, vol. 88, no. 4, (2008), pp. 844-857.
[9] Er. Neetu Bhatia," Optical Character Recognition Techniques: A Review", Kurukshetra institute of Technology & Management, Kurukshetra, , India, Bhatia, International Journal of Advanced Research in Computer Science and Software Engineering 4(5), May - 2014, pp. 1219-1223.
[10] MAJIDA ALI ABED HAMID ALI ABED ALASADI Simplifying Handwritten Characters Recognition Using a Particle Swarm Optimization Approach EUROPEAN ACADEMIC RESEARCH, VOL. I, ISSUE 5/ AUGUST 2013 ISSN 2286-4822.
[11] Mohammed Z. Khedher, Gheith A. Abandah, and Ahmed M. Al-Khawaldeh Optimizing Feature Selection for Recognizing Handwritten Arabic Characters PROCEEDINGS OF WORLD ACADEMY OF SCIENCE, ENGINEERING AND TECHNOLOGY VOLUME 4 FEBRUARY 2005 ISSN 1307-6884.
[12] Ivan Dervisevic Machine Learning Methods for Optical Character Recognition December 18, 2006.
[13] Diego J. Romero, Leticia M. Seijas, Ana M. Ruedin Directional Continuous Wavelet Transform Applied to Handwritten Numerals Recognition Using Neural Networks JCS&T Vol. 7 No. 1 April 2007.
[14] Chirag I Patel, Ripal Patel, Palak Patel Handwritten Character Recognition using Neural Network International Journal of Scientific & Engineering Research Volume 2, Issue 5, May-2011.
[15] Sushree Sangita Patnaik and Anup Kumar Panda Particle Swarm Optimization and Bacterial Foraging Optimization Techniques for Optimal Current Harmonic Mitigation by Employing Active Power Filter Applied Computational Intelligence and Soft Computing Volume 2012, Article ID 897127.

[16] Dileep Kumar Patel, Tanmoy Som1, Sushil Kumar Yadav, Manoj Kumar Singh," Handwritten Character Recognition Using Multiresolution Technique and Euclidean Distance Metric" JSIP 2012, 208-214.
[17] Vijay Laxmi Sahu, Babita Kubde Offline Handwritten Character Recognition Techniques using Neural Network: A Review International Journal of Science and Research (IJSR), India Online ISSN: 2319-7064 Volume 2 Issue 1, January 2013.
[18] Gurpreet Singh Chandan Jyoti Kumar Rajneesh Rani Dr. Renu Dhir," Feature Extraction of Gurmukhi Script and Numerals: A Review of Offline Techniques" IJARCSSE Volume 3, Issue 1, January 2013 pp 257-263.
[19] Majida Ali Abed, Hamid Ali Abed Alasadi," Simplifying Handwritten Characters Recognition Using a Particle Swarm Optimization Approac h" European Academic Research, Vol. I, Issue 5/ August 2013 pp 532-552.
[20] Argha Roy, Diptam Dutta, Kaustav Choudhury," Training Artificial Neural Network using Particle Swarm Optimization Algorithm" IJARCS SE Volume 3, Issue 3, March 2013 pp 43—434.
[21] Amir Bahador Bayat Recognition of Handwritten Digits Using Optimized Adaptive Neuro-Fuzzy Inference Systems and Effective Features Journal of Pattern Recognition and Intelligent Systems Aug. 2013, Vol. 1.
[22] Swagatam Das, Arijit Biswas, Sambarta Dasgupta, and Ajith Abraham Bacterial Foraging Optimization Algorithm: Theoretical Foundations, Analysis, and Applications Hindawi Publishing Corporation Applied Computational Intelligence and Soft Computing Volume 2012, Article ID 897127.
[23] Somaya A. S. Al-Ma'adeed, "Recognition of Off-line Handwritten Arabic Words", Thesis submitted to The University of Nottingham for the degree of Doctor of Philosophy, June 2004.
[24] Nawwaf Kharma. Maher Ahmed, & Rabab Ward, " A New Comprehensive Database of Hand-written Arabic Words, Numbers, and Signatures used for OCR Testing", E.C.E. Department, (289-) 2366 Main Mall, University of British Columbia, Vancouver BC, Canada. V6T 1Z4.
[25] Copyright © 1993-2014 Scott E Umbaugh@ Southern lllinois University Edwardsville, version 5.5d
[26] A. Al-Haj, "Combined dwt-dct digital image watermarking," Journal of Computer Science 3(9), pp. 740-746, 2007.
[27] Kannada, English, and Hindi Handwritten Script Recognition using multiple features, Proc. of National Seminar on Recent Trends in Image Processing and
[28] Pattern Recognition (RTIPPR-10), Editors: Dr. P. S. Hiremath et. al., Excel India Pub., New Delhi, ISBN: 93-80043-74-0, pp 149-152.
[29] N. Otsu, "A Threshold Selection Method from Gray-Level Histogram", IEEE Tansaction Systems, Man and Cybernetics, vol 9, no.1, pp.62-66, 1979.
[30] M. Jiansheng, L. Sukang, and T. Xiaomei, "A digital watermarking algorithm based on dct and dwt," in Proceedings of the 2nd International Symposium on Web Information Systems and Applications (WISA 2009)Nanchang, China, pp. 104-107.
[31] J. Alkhateeb, Word Based Off-line Handwritten Arabic Classification and Recognition, Ph.D. thesis, School of Computing, Informatics and Media, University of Bradford, 2010.
[32] Z. Razak, N. A. Ghani, E. M. Tamil, M. Y. Idris, N. M. Noor, R. Salleh, M. Yaacob, M. Yakub, and Z.B. Yusoff, "Off-line jawi handwriting recognition using hamming classification," Information Technology Journal 8(7), pp. 971-981, 2009.
[33] J. H. AlKhateeb, Jinchang R., Jianmin J., S. S. Ipson, and H. El-Abed, "Word-based handwritten arabic scripts recognition using dct features and neural network classifier", in 5th International Multi-Conference on Systems, Signals and Devices, 2008, pp. 1-5.
[34] JAWAD NAGI," Pattern Recognition Of Simple Shapes In A Matlab / Simulink Environment: Design And Development Of An Efficient High-Speed Face Recognition System", College Of Engineering University Tenaga Nasional , Thesis, M.Sc, 2007,pp (97).
[35] Keerti Keshav Kanchi," Facial Expression Recognition using Image Processing and Neural Network", International Journal of Computer Science & Engineering Technology (IJCSET), ISSN: 2229-3345 Vol. 4 No. 05 May 2013.