Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X

IJCSMC, Vol. 4, Issue. 10, October 2015, pg.403 – 412

RESEARCH ARTICLE

OFFLINE HANDWRITTEN SIGNATURE VERIFICATION SYSTEM USING NEURAL NETWORK

Hadeel J.Jriash[1], Nada A. Z. Abdullah[2]

[1]Department of Computer Science, Baghdad University, Iraq

[2]Department of Computer Science, Baghdad University, Iraq

[1] hadeeljabbir@yahoo.com; [2] nadaazah@scbaghdad.edu.iq

***Abstract*— The signature of a person is an important biometric attribute of a human being which can be used to authenticate human identity. Various complex methodologies in the past have been proposed for signature verification through feature extraction. This paper presents a new method for off-line handwritten signature verification that depends on a discrete Radon transform (DRT) as feature extraction, and probabilistic neural network (PNN) as a verifier. The proposed system discriminates between forgery and original signature. The proposed system has three main steps; pre-processing to enhance the signature image, feature extraction and verification using the probabilistic neural network. The system trained using English signatures dataset of 54 persons. Satisfactory results are obtained with 90% Accuracy of system, 10.0% equal error rate (EER), 8.7% false acceptance rate (FRR), 11.4 false rejection rate (FAR) for skilled forgeries on our independent database.**

***Keywords*—** Offline handwritten signature, verification, DRT, PNN.

I. INTRODUCTION

Signature is a special case of handwriting which includes special characters and flourishes. Many signatures can be unreadable. They are a kind of artistic handwriting objects. However, a signature can be handled as an image, and hence, it can be recognized using computer vision and artificial neural network techniques [1].

Signature verification is an important research area in the field of personal authentication. The recognition of human handwriting is important concerning about the improvement of the interface between human beings and computers. If the computer is intelligent enough to understand human handwriting it will provide a more attractive and economic man-computer interface. Approaches to signature verification fall into two categories according to the acquisition of the data: On-line and Off-line. Online data record the motion of the stylus while the signature is produced, and includes location, and possibly velocity, acceleration and pen pressure, as functions of time. Off-line data is a 2-D image of the signature. Processing Off-line is complex due to the absence of stable dynamic characteristics. The difficulty also lies in the fact that it is hard to segment signature strokes due to highly stylish and unconventional writing styles [2]. Both offline and online systems are used to detect various types of forgeries. Signature forgeries are classified as:

1. Random/simple or zero effort. The forger doesn't have the shape of the writer's signature, but comes up with a draw of his own
2. Simple /casual forgery. The forger knows the writers signature shape and tries to imitate it without much practice.
3. Skilled forgeries. This is where the forger has unrestricted access to genuine signature model and comes up with a forged sample.

In this paper new offline signature verification is presented. In the first step, pre-processing is initially applied to the signature, then radon transform is applied to the signature image with a set of angles to obtain feature vectors, and the results are fed into PPN classifier to verify the tested signature.

II. LITERATURE REVIEW

In [Coe 04] a system was developed to automatically authenticate offline handwritten signatures using the discrete Radon transform (DRT) and a hidden Markov model (HMM). In this work Used a database of 924 signatures from 22 writers, the proposed system achieved an equal error rate (EER) of 18% when only high-quality forgeries (skilled forgeries) are considered and an EER of 4.5% in the case of only casual forgeries [3].

[Ala08] presented a method for verifying handwritten signatures by using NN architecture. Various static (e.g., Height, slant, etc.) And dynamic (e.g., Velocity, pen tip pressure, etc.) Signature features are extracted and used to train the NN. The resulting system performed reasonably well with an overall error rate (OER) in 3:3% (2.0% FAR and 1.3% FRR), it was trained using five genuine signatures and one hundred zero-effort forgeries [4].

[Ooi10] proposed an offline signature verification based on discrete Radon transform (DRT), principle component analysis (PCA) and probabilistic neural network (PNN). The proposed method was able to achieve 1.51%, 3.23%, and 13.07% equal error rate (EER) for random, casual, and skilled forgeries respectively [5].

[Mar 10] presented a novel off-line signature verification system. An ensemble of HMM-based classifiers was trained, using both global and local Radon transform-based features. Local features are extracted from circular retinas, An EER of 8.89% was achieved, which compares favorably to an EER of 12.9% (an improvement of 31.1%) when only global features are considered [6].

[Rad12] proposed a new offline signature recognition system based on Radon Transform, Fractal Dimension (FD) and Support Vector Machine (SVM). In the first step, projections of original signatures along four specified directions with angles 0°, 45°, 90° and 135° have been performed using radon transform. Then, FDs of four obtained vectors are calculated to construct a feature vector for each signature. These vectors are then fed into SVM classifier for recognition of signatures. The results indicated that the proposed method has a high accuracy in signature recognition [7].

[Mad13] introduced a new approach for off-line signature verification and recognition that depends on an artificial neural network. Which discriminate between two classes (i) forgery and (ii) original signature. The results showed that the proposed algorithm more efficient than most of the existing techniques [2].

[Push13] presented a Novel technique of Signature Verification by combining Zernike moments with Radon transform values at different angles of projection from the user's Signature pattern and then forming a statistical state machine with Hidden Markov Model and PLS Regression. The results showed that the proposed system verifies signature with an accuracy of 98% with false acceptance rate of 8% [8].

[Adi14] introduced a method of handwritten signature verification using a neural network approach. The method used features extracted from preprocessed signature images. The extracted features are used to train a neural network using error back propagation training algorithm. The network could classify all genuine and forged signatures correctly. The correct classification rate of the system is 82.66% in generalization [9].

[PAL15] introduced a method for signature verification was done by means of image processing, geometric feature extraction and by using neural network techniques. For training and testing of the system many signatures are used. This method was able to achieve Accuracy about 86.25% [10].

III. THE PROPOSED VERIFICATION SYSTEM

Generally, an offline handwritten signature verification system includes data acquisition, pre-processing, feature extraction and encoding, as well as matching as shown in Fig. 1. These processes will be further discussed in the following sections.

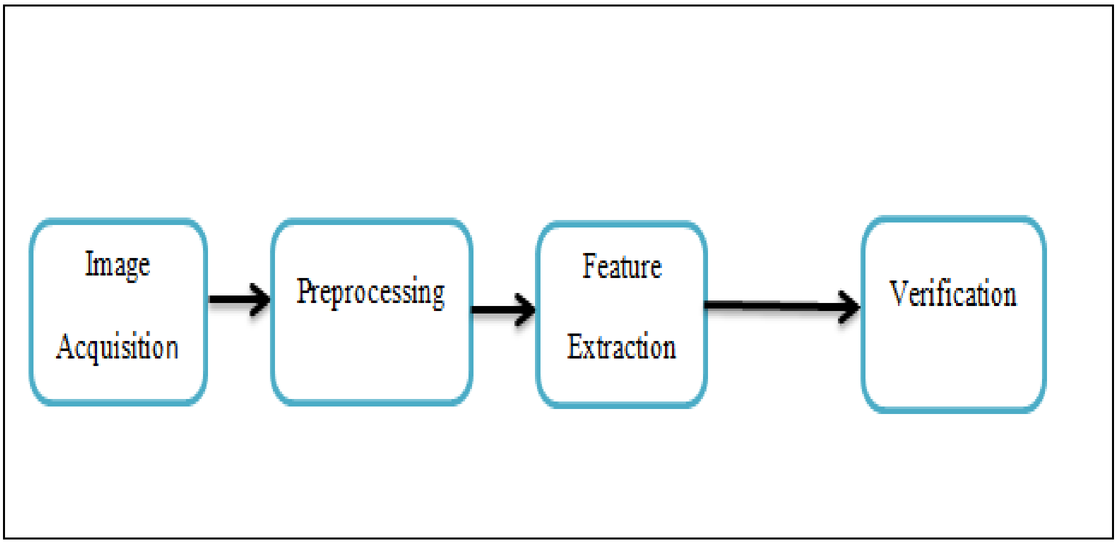


Fig.1 General Overview of Static signature verification system

A. Data Acquisition

In offline signature verification system, images of the signatures are scanned using a digital scanner. Scanned images are stored digitally for offline processing. [12]. In this work dataset consists of 55 original signatures and 55 forgery signatures each writer has 24 samples of his sign. Fig. 2. shows collection of database.

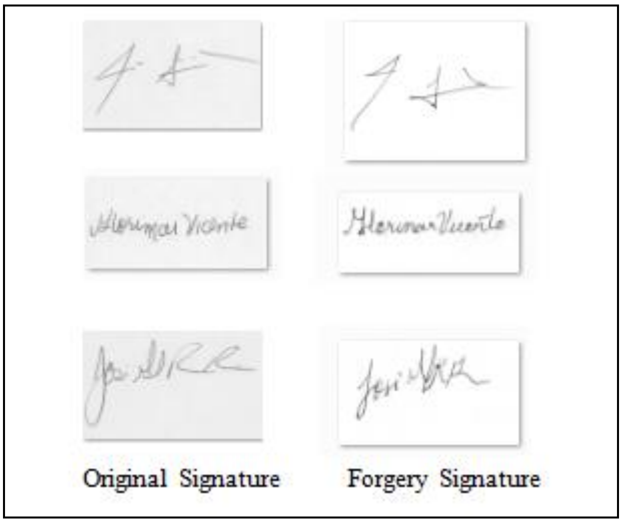


Fig.2 Collection of Database

B. Preprocessing

The purpose of this step is to make signature standard and ready for feature extraction. The pre-processing stage improves quality of the image and makes it suitable for feature extraction [13] .The preprocessing stage includes the following steps and Shown in Fig.3:

1) Convert the image into Gray

In present technology, almost all images capturing and scanning devices use color. Therefore, we also used a color scanning device to scan signature images. A color image consists of a coordinate matrix and three color matrices. Coordinate matrix contains x, y coordinate values of the image. The color matrices are labeled as red (R), green (G), and blue (B). Techniques presented in this study are based on gray scale images, and therefore, scanned or captured color images are initially converted to gray scale [14] using the following equation[15]:

$$\mathrm{gray}(x,y) = \frac{\mathrm{red}(x,y) + \mathrm{green}(x,y) + \mathrm{blue}(x,y)}{3} \qquad (1)$$

2) Contrast Stretching

Contrast stretching aims to improve the contrast in the low-contrast image that occurs due to poor illumination, lack of dynamic range in the sensor, or wrong lens setting. It operates by stretching the range of pixel intensities of the input image to occupy the whole dynamic range in the output image. Using the following equation [16]:

$$N(x,y) = \frac{O(x,y) - O_{\min}}{O_{\max} - O_{\min}} * 255 \qquad (2)$$

3) Noise Reduction

Noise reduction (also called “smoothing” or “noise filtering”) is one of the most important processes in image processing. Median filter is widely used for smoothing and restoring images corrupted by noise. It is a non-linear process useful especially in reducing impulsive or salt-and-pepper type noise. In a median filter, a window slides over the image, and for each positioning of the window, the median intensity of the pixels inside it determines the intensity of the pixel located in the middle of the window. Median Filter is used in this study due to its edge preserving feature [1].

4) Binarization

There are 256 gray levels of a gray scale image. We need a binaries image having only white and black values. Each pixel is stored as a single bit (0 or 1). [17] Working in this form is more useful than any other form, since it is easy to work with 2 bits representation of image. The required time to process colored image is longer than binary one [18]. We used adaptive thresholding technique for differentiating the signature pixels from the background pixels by using the following equations:

Min=mean-(Alpha*STD) (3)

Threshold=min (4)

Where the value of Alpha in equation 3 is either 1.4 or 2 based on the contrast of image. If the image is low contrast, the value of Alpha=2 otherwise the value of Alpha=1.4 that is for better result.

5) Cropping Signature Image

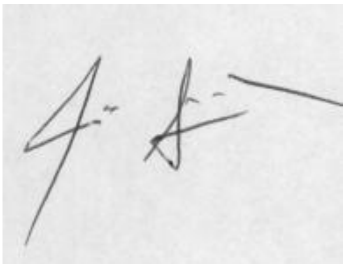
In this stage the Region of Interest (ROI) is determined using auto cropping approach. ROI is the signature object itself. Using cropping we segment the signature smoothly. Automatic cropping saves more work and reduces a processing time. The height and width of the first and last pixels in the signature are founded in this step to cut the signature.

6) Image resizing

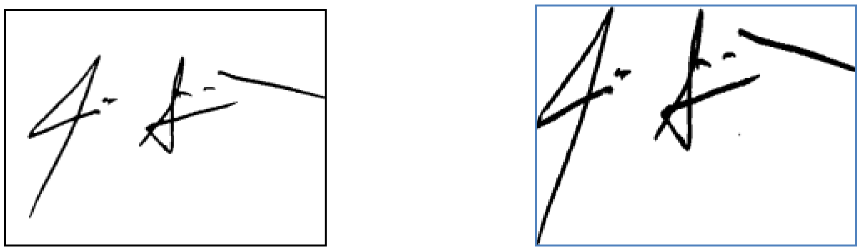
After clipping, height and width of signatures vary from person to person and, sometimes, even the same person may use different size signatures. First, we need to eliminate the size differences and obtain a standard signature size for all signatures. After this normalization process, all signatures will have the same dimensions. In this paper, we used a normalized size of 200x200 pixels for all signatures.

(a)

(b)



(c)



(d) (e)

Fig.3:(a) Original Signature. (b) Gray scale. (c) Denoising . (d) Binarization. (e) Cropping

C. Feature Extraction

Feature Extraction is the key process to achieve high accuracy in signature verification [19]. The features which we have extracted in the proposed system to generate feature vector that fed to PNN based on discrete Radon transform (DRT). This stage includes two steps: feature vector extraction using DRT for each signature image on different directions, then feature reduction.

1) Discrete Radon Transform (DRT)

In recent years the discrete radon transform have received much attention. The Radon Transformation is a fundamental tool which is used in various applications such as radar imaging, geophysical imaging, nondestructive testing and medical imaging [20]. DRT is chosen to transform the signature images into a feature space. The radon transform is projections of an image matrix along specified directions .A projection of a two-dimensional function f(x, y) is a set of line integrals. The radon transform computes the line integrals from multiple sources along parallel paths, or beams, in a certain direction. The beams are spaced 1 pixel unit apart. To represent an image, the radon transform takes multiple, parallel-beam projections of the image from different angles by rotating the source around the center of the image. Projections can be computed along any angle.[7]as shown in fig. 4.

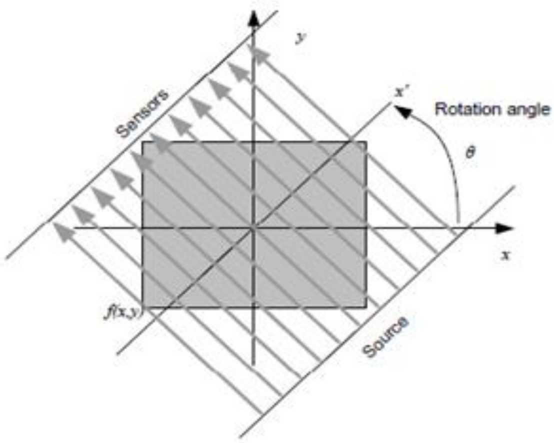


Fig.4 Single projection at a specified rotation angle.

Subsequently, the DRT of each signature is calculated, where each column represents a projection or shadow of the original image at a certain angle. After these projections are processed and normalized, they represent a set of feature vectors (observation sequence) for the signature.[21] DRT can be expressed as follows[3]:

$$Rj = \sum_{i=1}^{\Psi} WijIi;\ j = 1,2,\ldots, N\phi N\theta \qquad (6)$$

Where:

Rj= the cumulative intensity of the pixels that lie within the jth beam.

Ψ= total pixels in an image.

wij= the contribution of the ith pixel to the jth beam-sum.

Ii= the intensity of the ith pixel.

Nφ= non-overlapping beams per angle

Nθ= number of total angles

The DRT, as a feature extraction technique, has several advantages. Although the DRT is not a shift invariant representation of a signature image, shift and scale invariance is ensured by the subsequent image processing. Each signature is a static image and contains no dynamic information. Since the feature vectors are obtained by calculating projections at different angles, simulated time evolution is created from one feature vector to the next, where the angle is the dynamic variable.

2) Feature Reduction

Radon transform computes the line integral along parallel paths in a certain direction.

In this work, we computed line integrals of the signature image at 4 different directions. The 4 directions (orientations) from 0-180 degree with the interval of 45 and 30 degree have been selected empirically. Thus the feature vector size becomes 637×4 for each image. This approach for feature extraction gives us a long feature vector with 2548 elements that is inappropriate for classification purpose and take more memory to solve this problem, we reduction this feature vector by using mean _max method.

When used the interval of 45 the radon transform is applied on the signature image with angles (45°, 90°, 135°and 180°). Then used mean _max method by compute mean for each 10 values in each angle to become the feature vector size 64×4, then find the max value between four angle to become the size in the end 64×1.

In case of selected interval 30 the radon is perform with angles (45°, 75°, 105°and 135°). The mean-max method also applied, mean for each 10 values is computed but remove all zero value from each angle vector to become the length of feature vector 57×4 and find max ,thus 57×1 is the size of feature vector. The main advantage of this method, it compresses the data without much loss of information. takes less processing time and less space in memory.

D. Verification

In the verification stage, the system compares the extracted features from tested signature with the features extracted from the corresponding signature in the database in order to verify the authenticity of the signature and makes a final decision for verification as genuine or forged signature[10]. As verifier, in this paper the PNN is used. Among the main advantages that discriminate PNN is: Fast training process, an inherently parallel structure, guaranteed to converge to an optimal classifier as the size of the representative training set increases and training samples can be added or removed without extensive retraining.

1) Probabilistic Neural Network:

A Probabilistic Neural Network (PNN) is defined as an implementation of statistical algorithm called Kernel discriminate analysis in which the operations are organized into multilayered feed forward network with four layers: input layer, pattern layer, summation layer and output layer as shown in fig. 5. PNN learns more quickly than many neural networks model and have had success on a variety of applications. Based on these facts and advantages, PNN can be viewed as a supervised neural network that is capable of using it in system classification and pattern recognition. [22]

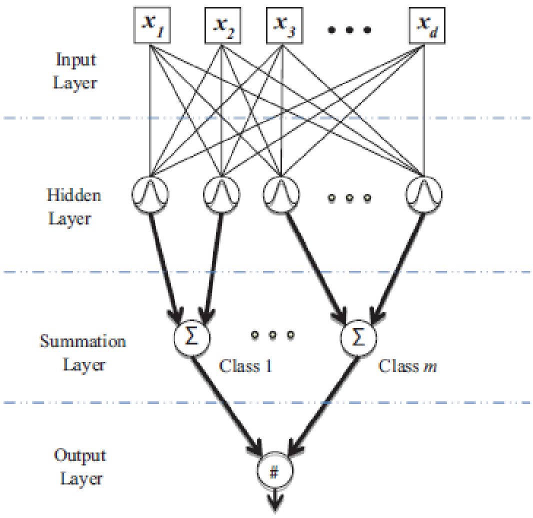


Fig. 5 PNN structure

IV. PERFORMANCE EVALUATION

The results provided in this research used a total of 2640 signatures. Those 2640 signatures are comprised of 55 sets (i.e. from 55 different people) and, for each person there are 24 samples of genuine signatures and 24 samples of forgeries. separating data into training and testing sets is an important part. Typically, when separate a data set into a training set and testing set, most of the data is used for training, and a smaller portion of the data is used for testing. Analysis Services randomly samples the data to help ensure that the testing and training sets are similar.

First, to train the system, a subset of this dataset was taken comprising of 14 genuine samples taken from each of the 55 different individuals and 14 forgeries made by different person for one signature. The features extracted from 14 genuine signatures and 14 forged signatures for each person were used to train a neural network. Then to test the system 10 authentic and 10 forged samples for every individual is used. The total testing set consists of 1100 samples. After training The PNN, the system tested to check the result of each tested signature to evaluate the performance of the proposed system.

In evaluating the performance of a signature verification system, there are two important factors: the false rejection rate (FRR) of genuine signatures and the false acceptance rate (FAR) of forgery signatures and these two are inversely related. The false rejection rate (FRR), the false acceptance rate (FAR), the equal error rate (EER), and Accuracy are used as quality performance measures.

As mentioned above, we use different number of feature vector length (according to the different angles used in DRT) 57 (when the angles used are (45°, 75°, 105°and 135°))and 64 (when the angles used are(45°, 90°, 135°and 180°)). as shown in Table I. The feature vector of length 64 gives better result than of 57 using PNN. It is interesting to discover that longer feature length leads to better result.

Table I. Proposed system Performance evaluation using PNN

Length of Feature vector	equal error rate(EER%)	False Acceptance Rate(FAR%)	False Rejection Rate(FRR%)	Accuracy rate%
57	11.90	12.72	11.09	88
64	10.0	11.4	8.7	**90**

Next, we investigate the performance of DRT by using (Euclidean) distance measure for skilled forgeries compared with PNN. The results illustrated in Table II for feature vector length 57and 64.

Table II Proposed System performance evaluation using PNN and Euclidean

method	Length of Feature vector	equal error rate(EER%)	FalseAcceptance Rate(FAR%)	False Rejection Rate(FRR%)	Accuracy rate%
PNN	57	11.90	12.72	11.09	88
Euclidean Distance	57	18.1	16.7	19.6	81.7
PNN	64	10.0	11.4	8.7	**90**
Euclidean Distance	64	15.6	16.7	14.5	84.6

As seen above PNN gives good results values compare to Euclidean distance.

V. CONCLUSIONS

This paper proposed a new method for off-line handwritten signature verification that depends on a discrete Radon transform (DRT), and probabilistic neural network (PNN).The high accuracy is feasible to filter the forgery from the genuine signature, especially for skilled forgery; while the speed of the PNN is very favourable in real-world application. The results are encouraging and thus should motivating the research on skilled forgery detection especially for offline handwritten signature, and use of additional features improving verification results and increasing feature dimensionality.

REFERENCES

[1] Cemil OZ, Fikret Ercal, Zafer Demir," Signature Recognition and Verification with ANN",Turkey,2003.

[2] M. D. Malekar,S.Patel," Off-line SignatureVerificationUsingArtificialNeuralNetwork ", International Journal of Emerging Technology and Advanced Engineering, Vol. 3, Issue 9, Sep 2013.

[3] J. Coetzer, B. M. Herbst, J. A. du Preez," Offline Signature Verification Using the Discrete Radon Transform and a HiddenMarkovModel ", EURASIP Journal on Applied Signal Processing 2004.

[4] A.McCabe, J. Trevathan and W.Read," Neural Network-based Handwritten Signature Verification ", JOURNAL OF COMPUTERS, VOL. 3, NO. 8, AUGUST 2008.

[5] O.Shih, A. Teoh," Offline Signature Verification through Probabilistic Neural Network",WSCG 2010.

[6] M. Panton, H. Coetzer," Off-line signature verification using ensembles of local Radon transform-based HMMs ", South Africa,2010.

[7] M.Radmehr, S.M.Anisheh, I.Yousefian," Offline Signature Recognition using Radon Transform ", World Academy of Science, Engineering and Technology,Vol:6, No:2, 2012.

[8] K. N. Pushpalatha , A. Kumar Gautham, D. R.Shashikumar," Offline Signature Verification with Random and Skilled Forgery Detection Using Polar Domain Features and Multi Stage Classification-Regression Model ", International Journal of Advanced Science and Technology ,Vol.59, (2013), pp.27-40.

[9] A. Kapil, J. Singh, V. Srivastava," A Hybrid Approach for Offline Signature Verification using Artificial Neural Networks", International Journal of Information & Computation Technology, Vol.4, No. 12 (2014), pp. 1113-1121.

[10] P.V.HATKAR,B.T.SALOKHE,"OFFLINE HANDWRITTEN SIGNATURE VERIFICATION USING NEURAL NETWORK"JOURNAL OF INFORMATION, KNOWLEDGE AND RESEARCH INELECTRICAL ENGINEERING,NOV 14 TO OCT 15 ,VOL – 03.

[11] S. Garhawal, N.Shukla," A Study on Handwritten Signature Verification Approaches ", International Journal of Advanced Research in Computer Engineering & Technology (IJARCET), Vol 2, August 2013.

[12] P. Kumar, S. Singh ,A. Garg ,N. Prabhat," Hand Written Signature Recognition & Verification using Neural Network ", International Journal of Advanced Research in Computer Science and Software Engineering, Vol 3, March 2013.

[13] Y.Moshtak,"Hand Written Hindi Numerals Recognition System",2011.

[14] M. Jasmine, K.Murugesan,S.R.Inbathini,A.Jabeena,K.S.Tej," Bank Cheque Authentication using Signature ", International Journal of Advanced Research in Computer Science and Software Engineering, Vol. 3, May 2013.

[15] B. Al-Mahadeen and M.S. AlTarawneh," Signature Region of Interest using Auto cropping ", IJCSI International Journal of Computer Science Issues, Vol. 7, No 4, March 2010.

[16] N.Rajpal ,B. Arora," A New Technique for Handwritten Offline Signature Authentication System ", International Journal of Advanced Research in Computer Science and Software Engineering, Vol 4, July 2014.

[17] S. Venturas, I. Flaounas," Study of Radon Transformation and Application of its Inverse to NMR", 4 July, 2005.

[18] A. ABDELRAHMAN, A. ABDALLAH," Signature Verification System Based on Support Vector Machine Classifier", The International Arab Conference on Information Technology , ACIT'2013.

[19] P. NAGESWARA, G. SRIDHAR and A. APPA," A PROBABILISTIC NEURAL NETWORK APPROACH FOR PROTEIN SUPERFAMILY CLASSIFICATION ", Journal of Theoretical and Applied Information Technology, Vol6. No1. (pp 101 - 105),2005 - 2009 .

