Offline Handwritten Signature Verification method based on Artificial Immune Recognition System and Artificial Neural Network

*Jasmeet Kaur[#1], Dr. Reecha Sharma[#2]
[#]Electronics and Engineering Department, Punjabi University
Corresponding Author: *Jasmeet Kaur

ABSTRACT
Natural immune system offers several fascinating options that motivated the planning of Artificial Immune Systems (AIS) accustomed solve varied issues of engineering and AI. AIS are significantly thriving in fault detection and diagnosing applications where anomalies like errors and failures are assimilated to viruses that ought to be detected. Thereby, AIS appear appropriate to automatically discover forgeries in signature verification systems. This paper proposes a unique technique for offline signature verification that's supports the artificial Immune Recognition System (AIRS) and ANN utilized in verification stage. For feature generation, 2 totally different descriptors are projected to get signature traits. the primary is that the Gaussian pyramid used for texture synthesis that is very redundant, coarse scales offer a lot of the data within the finer scales and Laplacian pyramid Seamlessly stitch along images into an image plaid (i.e., register the photographs and blurring the boundary), by smoothing the boundary in a very scale-dependent style to avoid boundary artefacts. The second descriptor is that the canny edge detector accustomed detects wide selection of edges in image. Performance analysis is administrated on GPDS-100 datasets. The results obtained showed that the proposed system has promising performance and infrequently well outperforms the state of the art.

Keywords: Artificial Immune Recognition System, Artificial Neural Network, Gaussian and Laplacian pyramid, canny edge detector.

Date of Submission: 10-07-2017 Date of acceptance: 20-07-2017

I. INTRODUCTION

Biometrics is the science which detects persons on the basis of their biological or behavioural features. Currently, various identification systems employing fingerprints, hand geometry, retina, iris, or faces provide very amusing performances. Nevertheless, in some specific applications using paper documents such as bank checks and contracts, handwritten signature remains the oldest and the main identification tool. Many successful studies have been reported on this subject. However, because of speed and robustness requirements, signature verification remains an open research issue [1].online and offline signature verification are two ways for developing such system[2].In the prior signature were taken using electronic device like tablets and instrumented stylus which nabbed information like x, y coordinates, velocity etc[3] but in offline signature we cannot attain such data as signature are transcribed on paper subsequently its less precise but it has large practical applications.

In the proposed work artificial immune recognition system and artificial neural network is used .AIRS is new research which stimulate biological behaviour ways like neural network. this system protect the system from any virus ,it will detect any foreign substance this process also includes both unchanged and un encountered organism[4].this helped to develop system which could solve expert and intelligent system problems like fault or anomaly detection. The AIRS algorithm was used for thyroid diagnosis, fault detection and watermarking. In this method ANN is used in the verification stage of signature verification as AIRS algorithm the ANN is mainly used for large number of data or users and have been widely used for forecasting and decision modelling problem.ANN are computational models which are inspired by organising and functioning of biological blocks.

This paper contribute two steps feature extraction and classification for feature extraction the Gaussian, Laplacian pyramid and canny edge detector is used and for classification in training AIRS is used and in verification stage the ANN is used. This paper is arranged as section 2 represents the background of signature verification methods.Section3 introduces proposed verification system. Experimental results are discussed in section 4 and last section gives main conclusion.

II. BACKGROUND

Online and offline signature method verification system has mainly two steps that are feature extraction and verification. In [5] model based approach for signature verification and for feature generation the structural form of signature were found using directional frontier feature and for verification statistical verification algorithm was used. The positional variation of strokes of signature for feature generation and accordingly the statics were made for the verification in [6]. Geometric signature feature for feature generation and SVM, HMM and Euclidean distance were used as classifiers for the promising results in [7]. In 2007 vertical projection were used for feature generation and dynamic time warping and modified DTW were used for verification [8]and used fusion system for the segmentation data using HMM for classification [9]. Graph metric feature was used for improving the performance of classification by decreasing the false acceptance [10]. In 2010 contour let transform was used for feature generation by finding contour let coefficients as feature extractor and then for classifier SVM was used[11] and used LCSS i.e. longest common sub sequence detection method for comparing of signature time series into a kernel function for support vector machines(SVM)[12]. In 2011 for texture feature based on grey level information uses global image level for measuring grey level variations then co-occurrence matrix and local binary pattern is used for feature extraction then for classification SVM was used [13] and geometric features like area, centre of gravity, eccentricity, kurtosis and skewness were used to extract feature then ANN was used for the classification to get the better result [14]. Surroundedness property on a novel set of feature based signature verification was used, in this feature set is unique as it contain shape and texture property for classification and to see the enhancement the SVM and the multilayer perceptron was used[15]. Envelope shape feature like chord moments and central moments such as mean ,variance, skewness, kurtosis, chord moment were used for feature extraction and SVM was used for classifier gave the good results[16]. An online signature verification technique which was suitable for mobile devices which made the system well protected and in this user specific classifier is used which can train large number of users [17]. Counter let transform and directional code co-occurrence matrix were used for feature extraction for verification one class protocol was used to get the good performance [18].In 2016 gradient local binary patters and longest run feature were used for feature generation and AIRS was used for classification and k-NN was used in verification stage to get the promising result [19].

III. PROPOSED WORK

The flowchart of proposed signature verification system is shown in figure 1.firstly the signatures are converted into binary format. Then in order to extract feature we used three feature generations technique fusion the fusion score is made then classification is done according to fusion score.

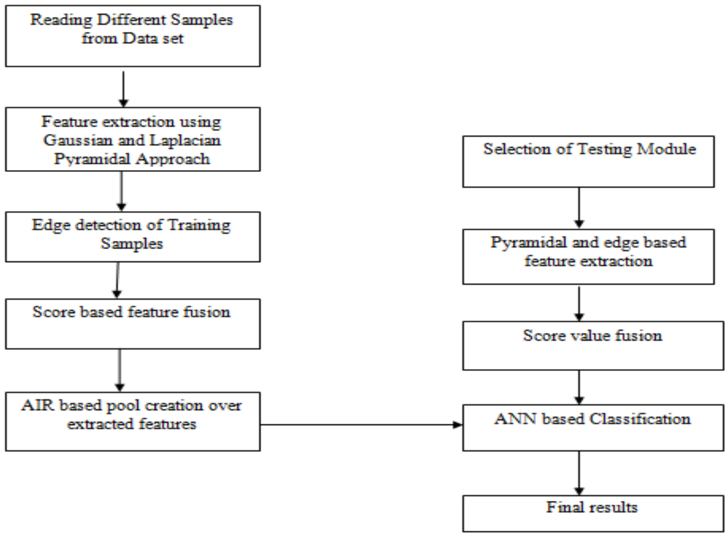


Figure 1: Flowchart of proposed work

1. Pre processing: Firstly the signature collected or the database is converted into the binary format using MATLAB command and then the signatures are read from the data set for the feature generation

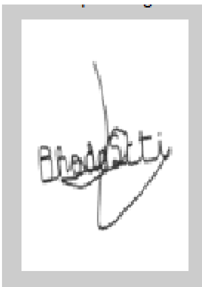


Figure 2: Binary signature

2. Feature Extraction:

2.1 Gaussian pyramid and Laplacian pyramid:

The principle of this method is to make sub images from the original image with different spatial resolution by using mathematical operations. The Laplacian pyramid is derived from the Gaussian pyramid and we drive Gaussian pyramid by recursive low pass filtering and decimation to make Laplacian pyramid firstly we will do Gaussian pyramid decomposition and then next step is to make Gaussian pyramid to Laplacian pyramid.

A. Gaussian pyramid decomposition

The zero level of pyramid is g_0 is egual to the source image , g_0 is the bottom level of the pyramid and the m-th level of Gaussian pyramid is g_m , which is obtained by following steps:1

Firstly the convolution is conducted between the m-1 th level images g_{m-1} with the window function $\omega(x, y)$ which has low pass characteristics, convolution results are separated out in the down sampling which is expressed as

$$g_m(i,j) = \sum_{x=-2y}^{2} \sum_{-2}^{2} \omega(x,y) g_{m-1}(2i + x, 2j + y) \tag{1}$$

$$1 \leq m \leq M\ ,\ 0 \leq i < R,\ \ 0 \leq j \leq C$$

M maximal level of pyramid, C_m and R_m represents column and row number of the m th level pyramid respectively, $\omega(x, y)$ is weighting function or generating kernel, that is a two dimensional 5x5 window function defined as

$$g_{m-1} = \frac{1}{256} \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix} \tag{2}$$

This process is standard reduce operation

$$g_m = Reduce(g_{m-1}) \tag{3}$$

Then the Gaussian pyramid is constituted by $g_0, g_{1,\ldots,} g_M$, where g_0 and g_M are the bottom and top layer respectively of Gaussian pyramid and total number of pyramid layer is M+1.

Figure 3: Results of Gaussian pyramid of level 1, 2, 3 respectively

B. Laplacian Pyramid Decomposition

Laplacian pyramid is the band pass filtered image which reduces the large number of redundant information from the Gaussian pyramid. The difference is calculated between the two adjacent images to get the band pass filtered image. The steps for decomposition of Laplacian pyramid are as follow:

g_m^* is image obtained by expanding g_m, g_m^* has the same size as the g_{m-1} so the amplification operator Expand can be used for expanding

$$g_m^* = Expand(g_m) \tag{4}$$

According to equation (3) the Expand operator is defined as:

$$g_m^*(i,j) = 4\sum_{x=-2y}^{2}\sum_{-2}^{2}\omega(x,y)g_m(\frac{i+x}{2},\frac{j+y}{2})$$

$$1 \le m \le M \ , 0 \le i < R, \ 0 \le j \le C \qquad (5)$$

Where,

$$g_m^*\left(\frac{i+x}{2},\frac{j+y}{2}\right) = \begin{cases} g_m\left(\frac{i+x}{2},\frac{j+y}{2}\right), \frac{i+x}{2}, \frac{j+y}{2} & are\ integers \\ 0 & others \end{cases} \qquad (6)$$

Set

$$\begin{aligned} lp_m &= g_m - g_{m+1}^* \quad &, \ 0 \le m < M \\ lp_M &= g_m &, \ m = M \end{aligned} \qquad (7)$$

Where, M is number of Laplacian pyramid levels. lp_m is the m th level image decomposed from laplacian pyramid, Expand operator inverse of Reduce operator. $lp_0, lp_1, \ldots\ldots, lp_M$ are the levels of the laplacian pyramid these are the difference between Gaussian pyramid image and the last level is interpolated and enlarge like band pass filtering.

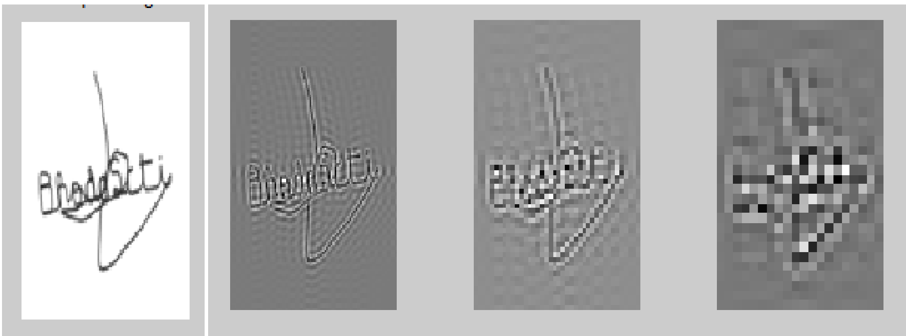


Figure 4: Results of Laplacian pyramid level 1, 2, 3 respectively

2.2 Canny Edge Detector

Canny edge detector is most popular edge detection algorithms it improves the edge detection method. Canny edge detector was designed to fulfil these criteria first was low error rate which is genuine edges should not be missed and spurious edges are not picked .Second was good localization that means pixels edges are found between the detector and the actual edge should be minimum and third is single edge point having only one response. First two doesn't eliminate multiple edges, so for this canny's edge was detected. Firstly image is smooth by the Gaussian filter .Then using multiple first derivative the image gradient is computed and then it highlight regions with high spatial derivatives. Algorithm tracks along the region of non maximum suppression and do not track the regions at maximum. The regions which were not suppressed are track using hysteresis. The first two thresholds lower T1 and upper T2 are identified and then points below the T1 are set to 0 means non edge and points above T2 are edge. Points magnitude between T1 and T2 are fixed to 0 expect there is a track from this point to a point gradient above T2.

$$\begin{aligned} p < T1 \qquad & non\ edges \\ p > T2 \qquad & edges \end{aligned} \qquad (8)$$

Where p are the points and T1 and T2 are the lower and upper threshold respectively. The performance depends upon number of parameters like σ, standard deviation,T1 and T2 .σ controls the size of Gaussian filter larger the scale of Gaussian filter the accuracy of localization of edge decreases and the smaller value decreases the amount of blurring and maintain finer edges. Canny algorithm performs better others in detecting all fine edges and localizing them correctly.

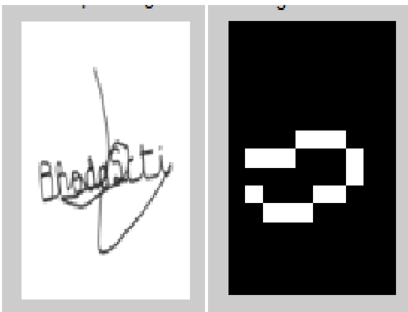


Figure 5: Results of canny edge detector

3. Classification:

3.1 Artificial Immune Recognition System:

Artificial immune systems are made from the natural immune system which uses antibodies B-cell to identify the dangerous invaders that is called antigens. It has various applications like feature generation, pattern recognition, machine learning and data mining. AIRS is algorithm which mimic immune symbols or parameters like antibody antigen binding, affinity maturation, clonal selection process, resource completion and memory cell acquisition. Each training or test sample is antigen. Antibodies which constitute data of each class are called memory cells (MC) of the system. As B-cell in AIRS is called as artificial recognition Balls (ARB) these corresponds to feature vector of an antibody with its class label and resource number. When train then AIRS develops new antibodies (or MC) which describes the different classes of interest. So ARBs compute for fixed number of resources with each other so that to keep high affinities to the training antigens. Affinity means similarity between patterns through Euclidian distance. From the remaining ARBs the new memory cells are extracted to form MC pool that will be used to classify test antigens. AIRS algorithm is as follow:
Affinity threshold is calculated

$$Naffinity(As,1) = \frac{\left(sum\left(min(GausP - LapP)\right)\right)}{R1 \times C1} \tag{9}$$

$$NAT(As,1) = \frac{mean\left(sum\left(sum\left(Naffinity(As,1)\right)\right)\right)}{(R1 \times C1)\frac{((R1 \times C1)-1)}{2}} \tag{10}$$

Where R1,C1 are row and column respectively, As are antigens, NAT is net affinity threshold, GausP is Gaussian pyramid , LapP is Laplacian pyramid, After affinity threshold is calculated then is the training process for antigens training in AIRS

$$NST(As,1) = 1 - mean\left(Naffinity(As,1)\right) \tag{11}$$

Where, NST is MC- match selection. Then generate the mutated clones of MC-Match and add them to ARBs pool. ARBs that belong to same class of present antigen will go for resource allocation and a selection process where as resource allocation means that each ARB is provided with a resource number to express how much simulation is high of antigen and the clonal selection is based on ARBs completion for a fixed global resource number so that only ARBs with high simulation are kept. To check the stopping condition the average simulation of ARBs of each class is calculated. If average simulation is less than user defined simulation threshold then above steps are repeated until we get desired result. Then the ARB with highest simulation is selected in the antigen class the (ARB is the memory cell-candidate).MC-candidate if have higher simulation then the present antigens then they are added to the Mc pool. Once all the antigens are trained then the new MC pool is used to classifying test samples. The classification is done by using ANN decision to compute MC pool.

3.2 Artificial Neural Network

ANN is mathematical models which are made by organising and functioning of biological neurons. According to the nature of the task assigned to the network there are numerous artificial neural network. There are variations according to how neurons are modelled. These models correspond closely to biological neurons and they depart from biological functioning in significant ways. Advantages of ANN upon other statistical methods, ANN is universal function approximates for even non linear function and also estimate piece wise approximation of functions.ANN uses one or more hidden layers, then network can partition the sample space automatically and then build different functions in different portion of that space. ANN is combination of more than one artificial neurons, neurons are organised in layers .Data travels form 1st input to the last after travelling the multiple layers. Each unit also have state with receiving and sending the data, state is represented by 0 and 1.ANN is typically defined by three parameters different layer of neurons, updating weights in learning process and activation function that to get output activation.

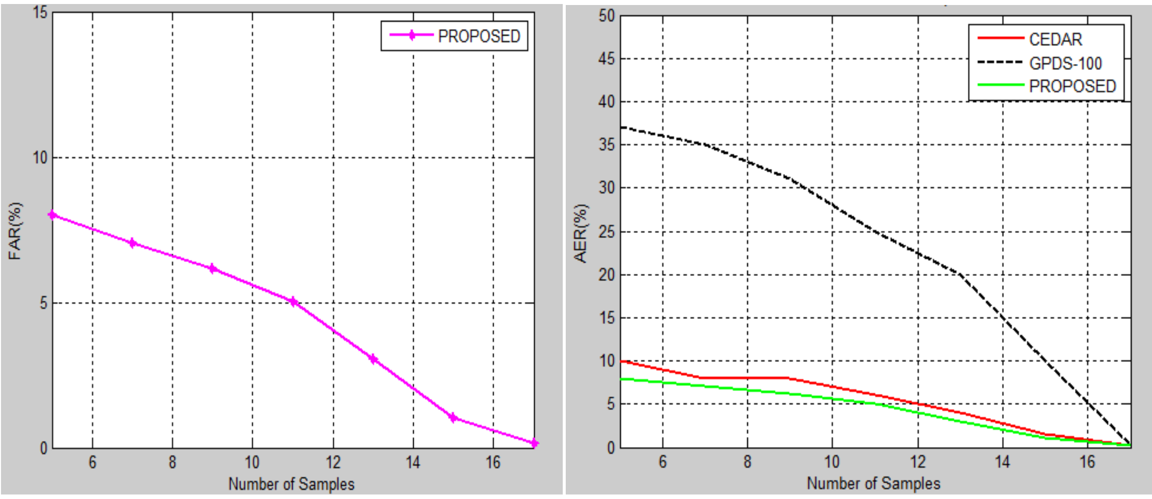
IV. EXPERIMENTAL RESULTS

The proposed signature verification system used the writer dependent where a specific system is implemented for each signer. The performance is evaluated based on False Rejection Ratio which is the percentage of true signature rejected by the system, False Acceptance Ratio which means number of forged signature accepted and Average Error Rate which provides global verification error. Experiments are conducted on GPDS-100 datasets

Performance evaluation

The performance assessment is based on feature for signature characterisation. Table 1 are the result obtained in the proposed method and shows the comparison with the previous methods. As FAR is less than FRR of the proposed system it means the system discriminates more forged signature. The FAR is 9.25 % and FRR is 10%

and the AER is 12.96% obtained from the proposed system with the dataset of GPDS -100.AIRS behaves well with proposed feature extraction techniques. So AIRS based verification gives comparable or sometimes better performance than others.



(a) (b)

Figure 6: (a) FAR variation and (b) AER variation for different number of samples

Table 1 Comparison of the proposed result obtained with existing technique

FEATURE	CLASSIFIER	GENUINE SIGNATURE	FRR %	FAR %	AER %
Surroundedness	MLP	24	13.76	13.76	13.76
GLCM	SVM	10	24.61	04.92	12.18
Geometric feature	Euclidian distance	16	16.39	15.50	15.94
Curvelet Transform	OC- SVM	12	12.50	19.40	15.95
Chain code histogram	SVM	12	13.16	09.64	11.40
Global traits; slant, width, length..	Structural similarity measure	15	09.62	15.82	12.72
Local interest points	bayesian		16.40	14.20	15.30
MDF, energy, maxima	SVM	12	17.25	17.25	17.25
GLBP+LRF	AIRS	16	11.38	13.16	12.52
Proposed	Proposed	22	10	09.25	12.96

V. CONCLUSION AND FUTURE WORK

This work proposes the use of Artificial Immune Recognition System and Artificial Neural Network for offline signature verification with the feature extraction fusion score of Gaussian pyramid, Laplacian pyramid and the canny edge detector. AIRS is method which do the learning mechanism of the natural immune system .It separates the normal behaviour in one class and abnormal behaviour in another class. AIRS are suitable for detection purpose like anomaly detection and fault detection than other classifiers in which training grants same processing for all the classes. Its training algorithm is easy because it is not based on error minimization. AIRS is main system of proposed offline signature verification system where antibodies are detected.

Experiments were conducted on public GPDS-100 datasets according to the approach. The comparison reveals that the proposed system can surpass existing methods. In the future this can be carried on by using the large number of datasets and signature in different language can be tried.

REFERENCE

[1]. Impedovo et al. "Handwritten signature verification by multiple reference sets. " In Proc. of the 11th International Conference on Frontiers in Handwriting Recognition (ICFHR), pp. 19-21. 2008.

[2]. Impedovo et al. "Automatic signature verification: The state of the art." IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews) 38, no. 5 (2008): 609-635.

[3]. Plamondon et al. 2000. Online and off-line handwriting recognition: a comprehensive survey. IEEE Transactions on pattern analysis and machine intelligence, 22(1), pp.63-84.

[4]. Bayar et al. 2015. Fault detection, diagnosis and recovery using Artificial Immune Systems: A review. Engineering Applications of Artificial Intelligence, 46, pp.43-57.

[5]. Huang et al. 2002. Off-line signature verification using structural feature correspondence. Pattern Recognition, 35(11), pp.2467-2477.

[6]. Fang et al. 2003. Off-line signature verification by the tracking of feature and stroke positions. Pattern recognition, 36(1), pp.91-101.

[7]. Ferrer et al. 2005. Offline geometric parameters for automatic signature verification using fixed-point arithmetic. IEEE transactions on pattern analysis and machine intelligence, 27(6), pp.993-997.

[8]. Shanker et al. 2007. Off-line signature verification using DTW. Pattern recognition letters, 28(12), pp.1407-1414.

[9]. Van et al. "On using the Viterbi path along with HMM likelihood information for online signature verification." Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on 37.5 (2007): 1237-124

[10]. Bertolini et al 2010. Reducing forgeries in writer-independent off-line signature verification through ensemble of classifiers. Pattern Recognition, 43(1), pp.387-396.

[11]. Soleymanpour et al. 2010, October. Offline handwritten signature identification and verification using contourlet transform and Support Vector Machine. In Machine Vision and Image Processing (MVIP), 2010 6th Iranian (pp. 1-6). IEEE.

[12]. Gruber et al. "Online signature verification with support vector machines based on LCSS kernel functions." Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on 40.4 (2010): 1088-1100.

[13]. Vargas et al. 2011. Off-line signature verification based on grey level information using texture features. Pattern Recognition, 44(2), pp.375-385.

[14]. Karouni et al. 2011. Offline signature recognition using neural networks approach. Procedia Computer Science, 3, pp.155-161.

[15]. Kumar et al. 2012. Writer-independent off-line signature verification using surroundedness feature. Pattern recognition letters, 33(3), pp.301-308.

[16]. Kumar et al. 2014. Off-line signature verification: upper and lower envelope shape analysis using chord moments. IET Biometrics, 3(4), pp.347-354.

[17]. Sae-Bae et al. "Online signature verification on mobile devices." Information Forensics and Security, IEEE Transactions on 9.6 (2014): 933-947

[18]. Hamadene et al. 2016. One-Class Writer-Independent Offline Signature Verification Using Feature Dissimilarity Thresholding. IEEE Transactions on Information Forensics and Security, 11(6), pp.1226-1238.

[19]. Serdouk et.al,, 2016. New off-line handwritten signature verification method based on artificial immune recognition system. Expert Systems with Applications, 51, pp.186-194.

International Journal of Computational Engineering Research (IJCER) is UGC approved Journal with Sl. No. 4627, Journal no. 47631.

Jasmeet Kaur. "Offline Handwritten Signature Verification method based on Artificial Immune Recognition System and Artificial Neural Network." International Journal of Computational Engineering Research (IJCER) 7.7 (2017): 78-84.