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Performance Evaluation Of Unsupervised Learning Algorithm In Biometric Based Fraud Prevention System

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ABSTRACT
Recently biometrics is the best alternative for the token based and knowledge based security systems. Unlike commonly used traditional identification technology based on passwords and keys, biometrics is more reliable, more convenient and more secure. Several algorithms have been employed, especially supervised learning algorithms, as data classifications. This paper implement unsupervised learning algorithm in multi-modal biometric system for its suitability. The system architecture consists of morphological pre-processing, feature selections, feature level fusion by concatenation, and matching stages. The performance of the Self Organizing Feature Map is compared with back-propagation neural network.
The processed data were matched for recognition using self organizing feature map and back-propagation neural network algorithms for performance. The back-propagation neural network produced recognition accuracy rate of 93.7, genuine acceptance rate of 98.4, and false acceptance rate of 7.7 while self organizing feature map yielded recognition accuracy rate of 93.5, genuine acceptance rate of 93.7, and false acceptance rate of 7.8. And it was deduced from the results that self organizing feature map relatively well as back-propagation neural network.
Keywords: ATMs, , Palm print, thumbprint, PSO, Self Organizing Feature Map

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I. INTRODUCTION

Biometrics is a fast growing technology which provides security to prevent unauthorized access to ATMs, computer networks, cellular phones, email authentication on multimedia workstations, PDA, etc. Crime which is happening in Automated Teller Machine (ATM) became a serious issue that affects not only customers but also bank operators. The main solution to this problem is multimodal biometrics. Biometric refers to the identification (or verification) of an individual (or a claimed identity) by using certain physiological or behavioural traits associated with the person. Biometric systems make use of hand, iris, finger, retina, palm, facial thermograms, signature or voiceprint to verify a person’s

identity [1]. Among the various biometric characteristics, the human hand is the oldest and the most successful form of biometric technology. The rich sets of biometric features that can be extracted from hand include: fingerprint, hand geometry, and palm print. [2]

Soft computing is a general term for describing a set of optimization and processing techniques that are tolerant of imprecision and uncertainty. The principal constituents of soft computing techniques are Fuzzy Logic (FL), Artificial Neural Networks (ANNs), Probabilistic Reasoning (PR), and Genetic Algorithms (GAs) [3]. The idea behind the application of soft computing techniques and particularly ANNs in implementing IDSs is to include an intelligent agent in the system that is capable of disclosing the latent patterns in abnormal and normal connection audit records, and to generalize the patterns to new (and slightly different) connection records of the same class.[4] Many of the algorithms employed for biometrics classifications are supervised in nature. However as the yearnings in improving security in ATM operations, there is need for more algorithms be experimented. This prompt the authors of this work to experiment with unsupervised learning algorithms to verify its effectiveness. Thus the main aim of this work is compare the performance of Self Organizing Feature Map (unsupervised) and back-propagation neural network (supervised) in multi-modal biometric system using thumb and palm traits.

II. RELATED WORKS

The section discusses past works being carried out by researchers. The emphasis is on the classifiers employed for each work. The authors in [5] proposed fusion method by using weighted sum rule and Support Vector Machine with Radial Basis Function kernel as classifier for palm print and hand geometry features. A recent paper by Han et al. [6] used morphological and Sobel edge features to characterize palm prints and trained a neural network classifier for their verification. The researchers in [7] proposed a biometric method that used hand geometry and palm print features computed from same image is used for authentication. Discrete Wavelet Transform (DWT) is used for feature extraction and Support Vector Machine (SVM) is proposed for classification. Experiments are carried out on the publicly available hand database. While [8] focused on an efficient methodology for identification and verification for iris detection, even when the images have obstructions, visual noise and different levels of illuminations. The proposed system employed Wavelet for image pre-processing, Gabor filter for feature extraction and the range of hamming distance as classifier for matching. [10] presented an efficient feature level fusion scheme applied on face and palmprint images. The features for each modality were obtained using Log Gabor transform and concatenated to form a fused feature vector. Particle Swarm Optimization (PSO) approach was used to reduce the dimension of the vector. Finally classification was performed on the projection space of the selected features using Kernel Direct Discriminant Analysis (KDDA). [11] presents a multimodal biometric verification system based on two features of palm and ear. They present a novel Feature selection algorithm based on PSO. The identification process can be divided into the following phases: capturing the image; pre-processing; extracting and normalizing the palm and ear images; feature extraction; matching and fusion; and finally, a decision based on PSO and GA classifiers. Also, previously, Euclidean distance, Manhattans distance, nearest neighbour (NN), the probabilistic decision-based neural network, hidden markov model and Probability Neural Network (PNN) [12, 13] been used as a classifier.

Self-Organizing Feature Map (SOFM)

The self-organizing feature map also known as a Kohonen map is a well-known artificial neural network. It is an unsupervised learning process, which learns the distribution of a set of patterns without any class information. It has the property of topology preservation. There is a competition among the neurons to be activated or fired. A SOFM network identifies a winning neuron using the same procedure as employed by a competitive layer. However, instead of updating only the winning neuron, all neurons within a certain neighbourhood of the winning neuron are updated using the Kohonen rule. The Kohonen rule allows the weights of a neuron to learn an input vector, and because of this it is useful in recognition applications.

The input vector p shown in Figure 1 is the row of pixels of the DCT compressed image. The ||ndist|| box accepts the input vector p and the input weight matrix $IW_{1,1}$, which produces a vector having S elements. The elements are the negative of the distances between the input vector and weight vectors (IW) formed from the rows of the input weight matrix. The ||ndist|| box computes the net input n of a competitive layer by finding the Euclidean distance between input vector p and the weight vectors as shown in Figure 1.

The competitive transfer function C accepts a net input vector for a layer and returns neuron outputs of 0 for all neurons except for the winner, the neuron associated with the most positive element of net input n^1. The winner's output is 1. The neuron whose weight vector is closest to the input vector has the least negative net input and, therefore, wins the competition to output a1. It was discovered that the competitive transfer function C produces output a1 for output element $a^1{}_i$ corresponding to 1, the winner. All other output elements in a^1 are 0.

$$n' = -\left\| IW_{1,1} - p \right\| \text{………1}$$

$a^1 = C(n^1)$……………….2

Thus, when a vector p is presented, the weights of the winning neuron and its close neighbours move toward p. Consequently, after many presentations, neighbouring neurons learn vectors similar to each other. Hence, the SOFM network learns to categorize the input vectors it sees. Figure 2.4 shows the flowchart of SOFM. The SOFM Algorithm is explained as follows:

1. Initialize weights W_{jk}^{o}, learning rate η^{o} and neighbourhood h_{jk}^{i}
2. Pick a sample x^i
3. Find out best matching neuron using Euclidean distance criterion

$$|| x^i - w_{jk}^i || = \min_{jk}\{||x^i - w_{jk}^i||\} \text{……3}$$

4. Update synaptic vectors of winning cluster

$$w_{i,jk}^{i \neq 1} = w_{i,jk}^{i} + \eta^{i}\left(x_i^i - w_{i,jk}^{i}\right) \quad jk \in h_{jk}^{i}$$

…..4

5. If noticeable change in mapping GOTO STEP 2 ELSE STEP 4
6. SOFM weight matrix

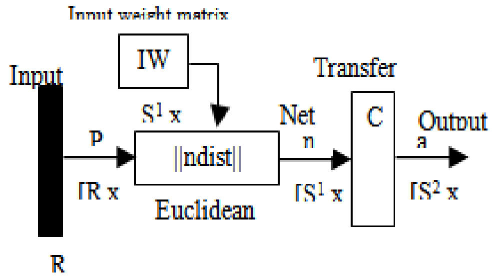


Figure 1: Architecture of a simple SOFM

[14] introduced self-organizing map, or SOM as an unsupervised learning process which learns the distribution of a set of patterns without any class information. A pattern is projected from an input space to a position in the map - information is coded as the location of an activated node. The SOM is unlike most classification or clustering techniques in that it provides a topological ordering of the classes. Similarity in input patterns is preserved in the output of the process.

III. THEORY OF NEURAL NETWORKS

Artificial neural networks were initially developed according to the elementary principle of the operation of the (human) neural system. Since then, a very large variety of networks have been constructed. All are composed of units (neurons), and connections between them, which together determine the behaviour of the network. The choice of the network type depends on the problem to be solved; the back-propagation gradient network is the most frequently used [16;17]. This network consists of three or more neuron layers: one input layer, one output layer and at least one hidden layer. In most cases, a network with only one hidden layer is used to restrict calculation time, especially when the results obtained are satisfactory. All the neurons of each layer (except the neurons of the last one) are connected by an axon to each neuron of the next layer (Fig. 2).

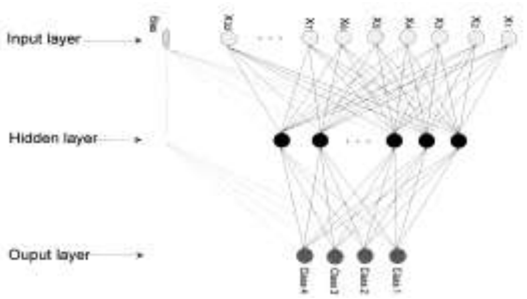


Fig. 2. Structure of a neural network as used in the experiments.

The input layer comprises n neurons (as shown in figure 3) that code for the n pieces of input signal ($X_1 \ldots X_n$) of the network (independent variables). The number of neurons of the hidden layer is chosen empirically by the user. Finally, the output layer comprises k neurons for the k classes (dependent variables). Each connection between two neurons is associated with a weight

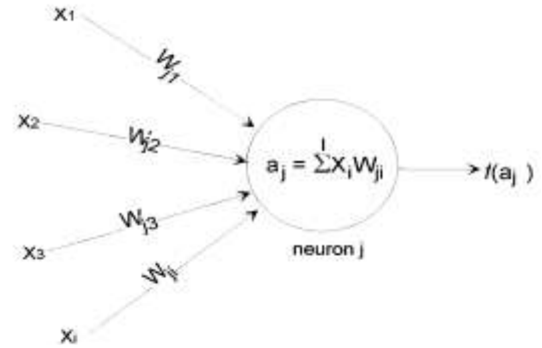


Fig. 3. Detail of one neuron

factor (random value between -0.3 and+0.3 at first); this weight is modified by successive iterations during the training of the network according to input and output data. In the input layer, the state of each neuron is determined by the input variable; the other neurons (hidden layer and output layer) evaluate the state of the signal from the previous layer (Fig. 2) as:

$$a_j = \sum_{i=1}^{I} X_i W_{ji} \quad \ldots\ldots.5$$

where a_j is the net input of neuron j; X_i is the output value of neuron i of the previous layer; W_{ji} is the weight factor of the connection between neuron i and neuron j. The activity of neurons is usually determined via a sigmoid function:

$$f(a_j) = \frac{1}{1 + \exp^{-a_j}} \quad \ldots\ldots\ldots6$$

Thus, weight factors represent the response of the NN to the problem being faced.

The back-propagation technique is akin to supervised learning as the network is trained with the expected reply/replies. Each iteration modifies the connection weights in order to minimize the error of the reply (expected value-estimated value). Adjustment of the weights, layer by layer, is calculated from the output layer back to the input layer. This correction is made by:

$$\Delta W_{ji} = \eta \delta_j f(a_i) \quad \ldots\ldots\ldots.7$$

where ΔW_{ji} is the adjustment of weight between neuron j and neuron i from the previous layer; f(ai) is the output of neuron i, η is the learning rate, and δ_j depends on the layer. For the output layer, δ_j is:

$$\delta_j = (Y_j - \hat{Y}_j) f'_j(a_j) \quad \ldots\ldots\ldots\ldots..8$$

where Y_j is the expected value ('observed value') and Y_j is the current output value ('estimated value') of neuron j. For the hidden layer, δ_j is:

$$\delta_j = f_j'(a_j) \sum_{k=1}^{K} \delta_k W_{kj} \quad \text{.............9}$$

where K is the number of neurons in the next layer. The learning rate plays an important role in training. When this rate is low, the convergence of the weight to an optimum is very slow, when the rate is too high, the network can oscillate, or more seriously it can get stuck in a local minimum [18]. To reduce these problems, a momentum term α is used and $\Delta W_{ji}^{\text{Prev}}$ becomes:

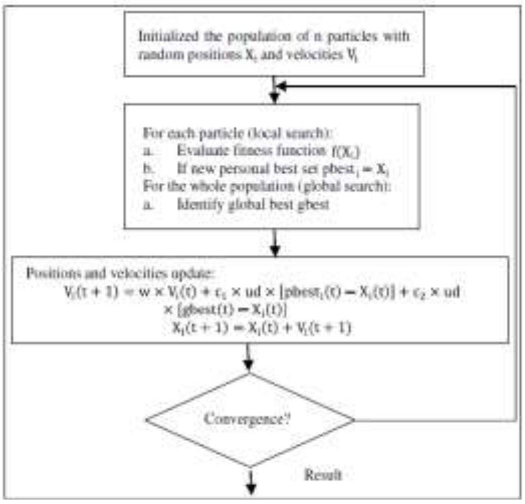
$$\Delta W_{ji} = \eta \delta_j f(a_i) + \alpha \Delta W_{ji}^{\text{Prev}} \quad \text{..........10}$$

where ΔW_{jt}^{prev} denotes the correction in the previous iteration. In this study, initially α=0.7 and η = 0.01, then they are modified according to the importance of the error.

IV. FEATURE SELECTION

After extraction of features, it has found that, within the extracted features, there are some features, which are irrelevant and noisy. These irrelevant and noisy features lead the misclassification rate. So the objective of feature selection step is to reduce the noisy data and exclude the irrelevant features as much as possible. In other word, find the optimal features from the original features including noisy and irrelevant features, which have higher discriminating power, to improve the recognition rate. Particle swarm optimization (PSO) is one such well-known tool to find the optimum characteristics with the help of local as well as global search in the feature search space in an iterative way. PSO proposed by [19]. In PSO, swarm consists of a group of random particles, which move around the solution space of the problem by updating through iterations for an optimum solution and go until convergence is achieved. A flowchart of the PSO-based system is given below:

Figure 4. PSO based feature selection



In this work, 'n' number of random particles is chosen initially from the features space. Each particle having c parameters that are obtained, after feature extraction using SIFT operator, and their corresponding random velocities form a position matrix X[n, c]. Now, the threshold should be selected for the first round of selection of these random velocities and its corresponding positions by the following functions V[i, j] = e(X[i, j]) where $1 \leq i \leq n$ and $1 \leq j \leq c$ and it is assumed to be 0.5 for this work. The velocity of the ith particle is described by the $V_i = (v_{i1}; v_{i2}; \ldots; v_{ic})$, and its corresponding state is represented by $X_i = (x_{i1}; x_{i2}; \ldots; x_{ic})$. If the newly computed velocity is greater than the threshold value (0.5), then this velocity and its location is selected for the next iteration. It is expected that, after each iteration, the recognition rate of the face recognition system increases with the newly selected features from the features space. So the success rate is calculated by an objective function known as the fitness function in PSO. The minimum distance function [20] is used here as a fitness function for this work. Here, minimum distance classifier concentrates both local and as well as global information of the features obtained from SIFT operator. The fitness function is evaluated for each particle in the swarm and is compared to the fitness of the best previous (pbest) result for that particle and to the fitness of the best particle (gbest) among all particles in the swarm. After finding the two best values (pbest and gbest), the particles start updating their velocities and positions according to the Eqs. (11) and (12), respectively.

$$V_i(t+1) = w \times V_i(t) + c_1 \times ud \times [pbest_i(t) - X_i(t)] + c_2 \times ud \times [gbest(t) - X_i(t)] \quad \text{.......(11)}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (12)$$

where 'i' = 1, …, n and 'n' is the population size, 'ud' is another random number between 0 and 1, 'c1' and 'c2' are cognitive and social parameters, respectively, bounded between 0 and 1. In the velocity update equation, the + sign divides the whole equation into three components named as inertial component, a cognitive component, and social component, respectively. The inertia weight w is a factor used to control the balance of the search algorithm between exploration (= 0.15) and exploitation (=1); the second element is the 'cognitive' section representing the local knowledge of the particle itself; the third component is the 'social' part, representing the cooperation among the particles. The iterative steps will go on until the process reaches the termination condition. It is experimentally found that thirty iterations are well enough to identify the optimum features from the features space, which leads the success rate to a great extent.

V. METHOD

Palm print pattern is not easily seen in visible light and thus cannot be captured by ordinary camera. Therefore, near infrared CCD (Charge-coupled device) sensitive camera and thumbprint reader was used to capture forty individuals' palm print and thumbprint respectively.

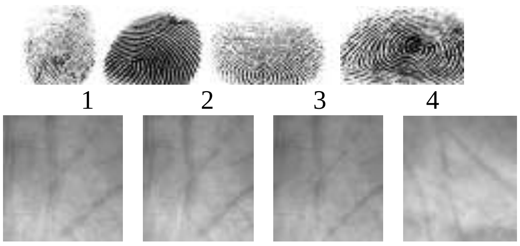


Figure 5. Samples of captured palmprint and thumbprint dataset

The multimodal biometrics algorithm consists of palm print and thumbprint templates generation and recognition, palm print and thumbprint recognition and fusion algorithm. The palm print and thumbprint templates were pre-processed morphological operations like; edge detection to mask shrink region of the noise removal on palm print images by Sobel gradient; and palm alignment for aligning palm poses to a standard pose to reduce the disturbing of nonlinear factors such as rotation, translation and distortion in sampling process. Thumbprint thinning is usually implemented via morphological operations such as erosion and dilation to reduce the width of ridges to a single pixel while preserving the extent and connectivity of the original shape. In order to extract similar features from two different impressions from the same thumb, they should be appropriately aligned before feature extraction.

Feature selection involves selecting salient palm print and thumbprint region of interest. PSO algorithm can be used to extract the rich line features of palm print and thumbprint. The fusion of the extracted features was done by concatenation, that is, merging up of features selected from palmprint (A) and thumbprint (B) to form new image C that is (A+B=C). The matching was done by employing back-propagation neural network and self-organizing feature map algorithms.

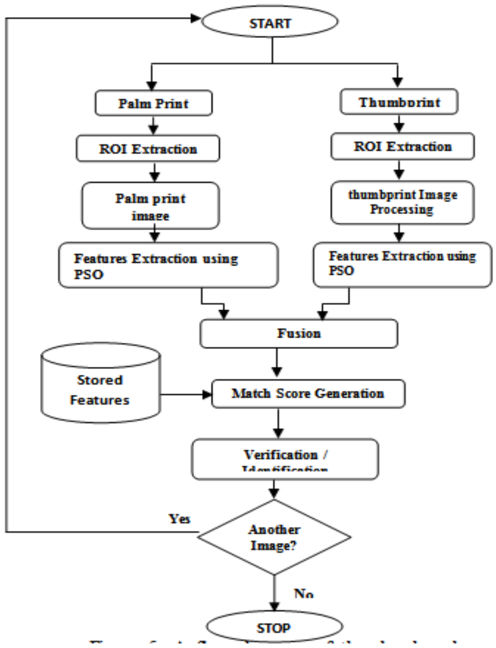


Figure 5: A flow diagram of the developed system

VI. RESULTS AND DISCUSSION

The graphical interface of the bimodal system consists of the captured sample stage and authentication stage as shown in figure 6. The images was acquired in 256RGB colours (8 bits per channel) format, with resolution of 640 x 480 pixels and 260 x 300 pixels for palm print and thumbprint respectively. For each individual, five palm print and thumbprint images will be captured (40*5*2 equals 400 images).

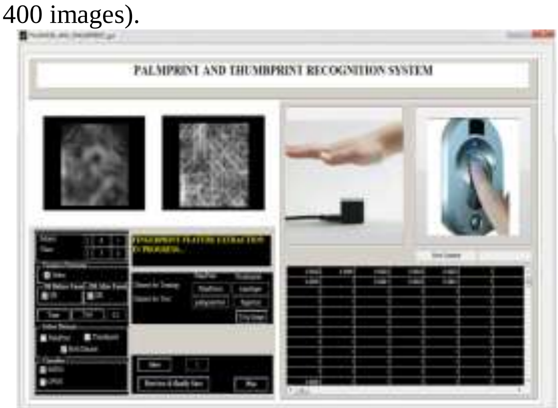


Figure 6. Graphical Interface of the Multimodal System

Recognition or classification of the images belonged to any of true positive, false positive, false negative or true negative was determined by threshold. The system was experimented using threshold value 0.5. The performance of the system was evaluated by applying the classifiers on feature fusion of palmprint and thumbprint. The total image acquired is 40 x 5 = 200. Trained images used (30 x 3) = 90. Test Images used 110 (i.e. (30 x 2) = 60 for genuine and (10 x 5) = 50 for impostor). The back-propagation neural network produced recognition accuracy rate of 93.7, genuine acceptance rate of 98.4, and false acceptance rate of 7.7 while self organizing feature map yielded recognition accuracy rate of 93.5, genuine acceptance rate of 93.7, and false acceptance rate of 7.8.

VII. CONCLUSION

This work has been able to carry out effectively the performance of unsupervised algorithm, self organizing feature map, in the implementation of multimodal recognition system. The accumulated data were subjected to necessary treatment viz; morphological pre-processing, feature selections, feature level fusion by concatenation, and matching. The processed data were matched for recognition using self organizing feature map and back-propagation neural network algorithms for performance evaluation. And it was deduced from the results that self organizing feature map relatively well as back-propagation neural network.

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