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Robust Multimodal Biometric System using Liquid State Machines

S.Belhia, A.Gafour, R.Adjoudj

EEDIS Laboratory,Computer Science Department University of Djillali Liabes,Sidi Bel Abbes, Algeria.

Abstract: An implementation of the recently proposed concept of the Liquid State Machine using a Spiking Neural Network (SNN) is trained to perform fingerprint and face recognition. The Liquid State Machine (LSM) can be used for pattern classification, function approximation and do the complex tasks. In this paper, the fusion of two uni-modal biometric verification systems is proposed. This have been done based on face and fingerprint. Gabor filters are applied to both the face and fingerprint in order to extract parameters which are then used for classification process. The fusion of modalities is situated at the feature extraction level by concatenating the vectors relative to each modality. Finally the feature vector is matched with stored template using machine learning methods. The suggested approach is original since it is based on liquid state machine which gives a better simulation of biological neurons as spiking neurons than sigmoidal ones Performance Evaluating has proved that liquid state machine achieved a good recognition rate closer to rates achieved by other methods but in a very short time.

Keys words: Fusion, Face, Fingerprint, Liquid State Machines, Multimodal Biometrics.

INTRODUCTION

The biometric technology has attracted more and more attention recently. As a result of the traditional recognition methods have some limitations, like inconvenience, unsafe and unreliable whereas biometric identification doesn't have these disadvantages. People's biometric features, like face and fingerprint are not only change less for life but also can't lose or forget and can overcome the limitations of traditional recognition methods. However, single modal biometric technology has reached a bottleneck and people show more and more attention to multi-modal biometric technology now. The multi-modal biometric technology makes up for the single biometric recognition which can be easily deceived .Multi-modal biometric technology which can use complementary information between different modals to improve the recognition rate has four levels, image level, feature level, score level and decision level .This paper focuses on the integration of feature level.(Yao Fu and *et al*, 2008), one important branch is to perform fusion in feature level which can derive the most discriminative information from original multiple features sets and eliminate the redundant information resulting from the correlation between different feature sets. The data obtained from each sensor is used to compute a feature vector. Two vectors are concatenated into a single new vector. The new feature vector now represents a person's identity in a different data space (Wang and *et al*, 2011). Due to this reason, we proposed a multimodal biometric system at the feature level fusion which combines two modalities face and fingerprint.

Various architectures have been used for performing such classifications. There is usually a training phase where the classifier is given valid feature vectors and their associated identity tokens.

The model of LSM is based on strict mathematical framework that guarantees, under ideal conditions, (GWojcik and Kaminski, 2003). We explore the application of liquid state machines (LSMs) to face, and fingerprint recognition. This paper mainly discusses the fusion of face and fingerprint biometrics. However, the algorithm and analysis presented here can also be applied to other multimodal biometric fusion applications (Belhia, 2012).

Methodology:

This paper mainly discusses the fusion of face and fingerprint biometrics. However, the algorithm and analysis presented here can also be applied to other multimodal biometric fusion applications (Belhia, 2011). Here Figure 1 illustrates a typical multimodal biometric authentication system. It consists of three main blocks that of pre-processing feature extraction and fusion.

1. Input the face and fingerprint image.
2. Selected features texture using Gabor.
3. The features are merged by concatenation technique.
4. Nearest neighborhood algorithm with Liquid State Machine is used for classification of image.
5. The test image is classified and the score of matching is calculated and the matched image is taken as output (Belhia, 2012), (see figure 1).

Corresponding Author: EEDIS Laboratory, Computer Science Department, Djillali Liabes University, Sidi Bel Abbes, Algeria.
E-mail: Belhia_souad@hotmail.com

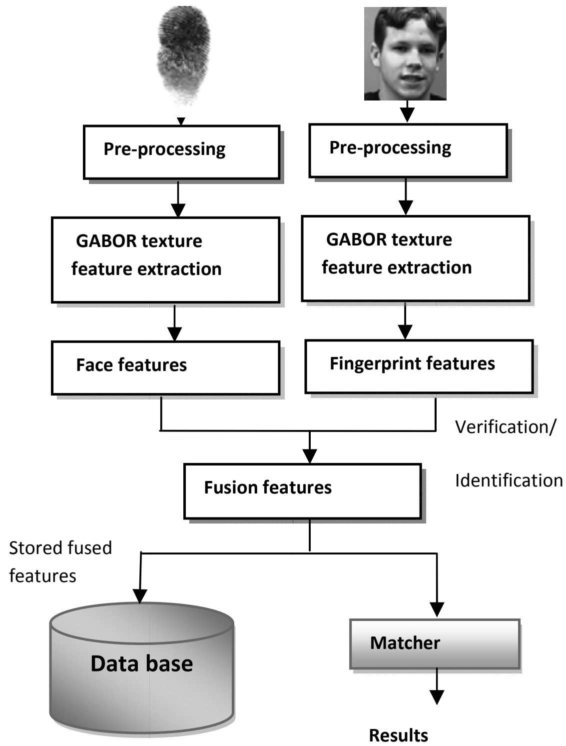

Fig. 1: Block diagram of face and fingerprint multimodal biometric

Creating codes:

A. Face code:

As one of the biometric technologies that possess the merits of both high convenience and low intrusiveness, face recognition has the wide application fields such as information security, law enforcement and surveillance, smart cards, access control. As a result, numerous face recognition algorithms and surveys have been presented (Sun.Q and *et al*, 2005, Valentin D and *et al*, 1994) one of the popular approaches for face feature extraction is Gabor filter (Wang. Z *et al*, 2011).

Gabor Filter for Feature Extraction:

Gabor transformation is a good simulation of the outline of single-cell receptive field in the cerebral cortex. It can also capture prominent visual properties, extract multi-scale, multi-direction space frequency features and enlarge the gray variety as microscopes therefore; therefore is very suitable to extract rich line features of face.

Annular Gabor transformation is shown in formula (1),

$$G(x,y;f,\theta) = \exp\left\{\frac{-1}{2}\left[\frac{x'^2}{\delta_{x'}^2}+\frac{y'^2}{\delta_{y'}^2}\right]\right\}\cos(2\pi f x') \quad (1)$$

Where

$$x' = x\sin\theta + y\cos\theta \qquad y' = x\cos\theta + y\sin\theta$$

f is the frequency of the sinusoidal plane wave, θ_k is the orientation of the Gabor filter, and σ_x, σ_y, are the standard deviations of the Gaussian envelope along the *x* and *y* axes, respectively. In order to extracting useful features from an image, a set of Gabor filters with different frequencies and orientations are required. Face recognition is friendly and non-invasive but its accuracy is affected by illumination, pose and facial expression. Face recognition systems must be robust to these variations. The pre-processing phase is simpler for the face case: the Acquired image is just resized to 128 ×128 pixels and transformed to a gray level image. The face processing chain is the same as the fingerprint: after pre-processing, the gray level images are convolved with a Gabor filter , whose parameters have been chosen empirically. The result is then vector of 256 elements to represents a face image. The new feature vector now represents a person's identity.

B. Fingerprint code:

Identification by fingerprints relies on pattern matching followed by the detection of certain ridge characteristics, also so known as Galton details, points of identity, or minutiae, and the comparison of the relative positions of these minutiae points with a reference print, usually an inked impression of a suspect's print. There are three basic ridge characteristics, the ridge ending, the bifurcation and the dot or island (see figure 2)

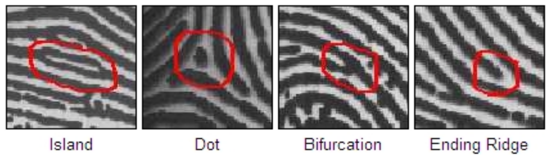

Fig. 2: Basic and composite ridge characteristics (minutiae)

Following steps are observed to create the finger code:

- Pre-processing of the image (to remove noise) by window wise normalization, Histogram Equalization, low pass and median filtering.
- Core point location using max concavity estimation (see figure 3).
- Tessellation of circular region around the reference point. (Y.Elmir *et al*, 2012).

Gabor filter based features have been succefully and widely applied to texture segmentation face recognition, handwriting recognition and Fingerprint enhancement, this is because the characteristics of the Gabor filter especially the frequency and orientation representations (see Figure 3) are similar to those of the human visual system. In this work we use Gabor filter based features directly extracted from grey level fingerprint images (with size 128X128 pixels) as the input vectors to a liquid state machine (LSM) classifier.

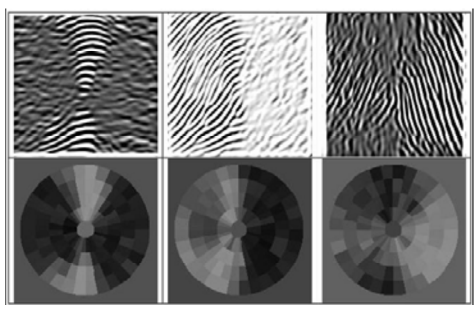

Fig. 3: Filtered images and their corresponding feature vectors for the orientations 0°, 5°.22.5° and 45° are shown (Muhammad.U and Muhammad, 2004).

Multimodal Fusion:

Fusion Strategies:

Our methodology for testing multimodal biometric systems focuses on the feature level fusion. This methodology has the benefit of exploiting more amount of information from each biometric.

The feature vectors are extracted independently from the pre-processed images of face, and fingerprint using Gabor texture feature.

These features are fused and stored as a parameter for finding the matched image from the database.

Feature level fusion is accomplished by a simple concatenation of the feature sets obtained from multiple information sources. Let $X = \{x_1; x_2; \ldots\ldots x_m\}$ and $Y = \{y_1; y_2; \ldots\ldots y_n\}$ denote feature vectors ($X \in R^m$ $Y \in R^n$) representing the information extracted via two different sources. The objective is to combine these two feature sets in order to yield a new feature vector, Z. that would better represent the individual. (Rossa and Govindarajanb, 2005).

The feature vectors of input images are then compared with the templates of the database to produce the output.

Combining more than one biometric modality progresses the recognition accuracy, reduces FAR and FRR. The proposed multimodal biometric system overcomes the limitations of individual biometric systems and also meets the accuracy requirements (Gayathri, 2012), (see figure 4).

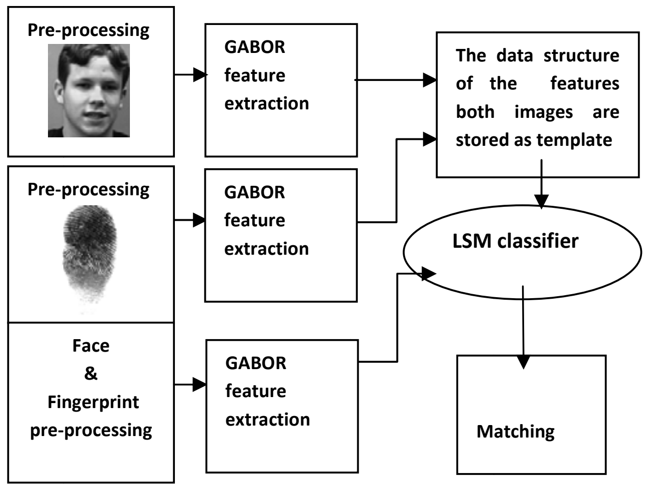

Fig. 4: Proposed automatic multimodal biometric system

Recognition:

The Liquid State Machine:

To achieve the treatment of varied temporal data flows, W.Maass and his colleagues (Maass *et al*, 2002a) proposed a working schema that advantages the rich dynamic of SNN called the Liquid State Machine which allows for real-time computing by employing continuous perturbations in a heterogeneous dynamical system. The basic idea of this model is to use a high dimensional dynamical system and have the inputs continuously perturb it. If the dynamics are sufficiently complex, the LSM should act as a set of filters projecting the inputs into a higher dimensional space. The LSM uses the internal dynamics of a recurrent spiking neural network to carry out computations on its input. The internal state of the SNN (called the liquid) serves as input for the so-called readout function. The liquid itself does not generate any output; it merely serves as a 'reservoir' for the inputs. The readout then looks at the liquid state (the response of the liquid to a certain input), and computes the output of the LSM.

The communication between the neurons in the liquid is done through the use of spikes. This means that the output from the system front ends needs to be converted from analogue values into a series of spike trains; for that, we use a LIF neuron as a way to code the analogue values into spike trains: this biologically realistic model of a real neuron takes an input current (an analogue value) as input, and produces spikes in response to this current. This coding scheme is computationally the most intensive due to the complexity of the model (Maass *et al*, 2002b).

A Liquid State Machine comprises three parts:

- The first part permits to present an entry to the network; it is used to transform some analogue data in pulse trains.
- The second part, or «liquid filter», does a memorization of the entries as well as a projection in a space of higher dimension.
- The third part is a reading card that permits to extract from the state of the network, in one given instant, information determined by training (Verstraeten *et al*, 2005).

We tried to implement this type of neurons networks to see its efficiency in the recognition of individuals by their faces and fingerprint. The global architecture of the network is described in (Figure5).

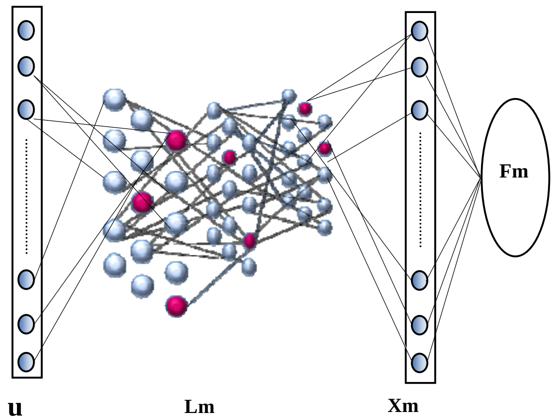

Fig. 5: The LSM architecture.

The network is composed of an entry layer U of 512 neurons (face + fingerprint) whose role is to transform the entries in pulse trains, a layer Lm that is a recurrent network of 3×3×15 LIF neurons and which serves like a dynamic reservoir, and an output layer Fm that permits the learning of an output y according to the X_m states of the network. The database of codes, generated after the coding by the Gabor filter of pretreated images of data fusion in vectors of features of a size equal to 512, is presented to the layer U which is going to transform those data in pulse trains that are going to act as stimuli to the main network Lm.

This network doesn't have a preconceived architecture or organization and its connectivity is partial and recurrent, it is called "dynamics reservoir" or "liquid". Every synaptic connection between a neuron i toward a neuron j is characterized by a weight w_{ij} and an axonal delay d_{ij}. The step of system training is done on the output layer, we opted for the back propagation of gradient algorithm, For the method this algorithm a MLP network of only one hidden layer, is added at the output of the network having as entries the states resulting from the LSM and as outputs the desired y_i (Verstraeten *et al*,2005).

Experiments and Results:

The effectiveness of our proposed multimodal biometric authentication scheme is evaluated on face database and fingerprint database.

Face Data Base:

The proposed algorithms have been evaluated on “Libor Spacek” data base .We have chosen 80 pictures of " .jpeg " format, with resolution 120by200; that contain the women and the men with glasses and beards, a green background Contains pictures of people of several racial origins, the majority of individuals to between 18-20 years .There are variations in facial expression and facial details (see Figure 6).

Fig. 6: Samples face images.

Fingerprint Data Base:

In order to assess the performance of the proposed system identification the FVC2004 data base (Third Fingerprint Verification Competition) was used. The different experimentations have been done on a data base constituted of 400 pictures of format ". tif " corresponding to 80 individuals, each having provided 3 samples that represent the basis of training and 2 samples represent the basis of test(see Figure 7) , (Maio *et al*, 2004).

The experiments are conducted in MATLAB with image processing Toolbox and on a machine with an Intel core 2 Duo CPU processor.

Fig. 7: Examples of fingerprints from FVC2004 databases

Results:

Table 1 explains the comparisons of two biometric systems (Face, Fingerprint, and "Face and Finger feature fusion") and their respective recognition percentage. The Table proves the advantages of multimodal biometric system through its performance (98.73%) and robustness evaluation by using more number of biometrics for person authentication.

From (Figure 8), it was observed that the experimental results demonstrated that the proposed multimodal biometric system achieves a recognition accuracy of 98.73 % and with means squared error (MSE) of = 0.012639.

Table 1: Table Below Summarises The Experimental Results For Our System

Biometric recognition system	Recognition Rate	Mean Squared Error (MSE)
Face	69.73%	0.302687
Fingerprint	93.04%	0.069531
Feature fusion (Face and Fingerprint)	98.73%	0.012639

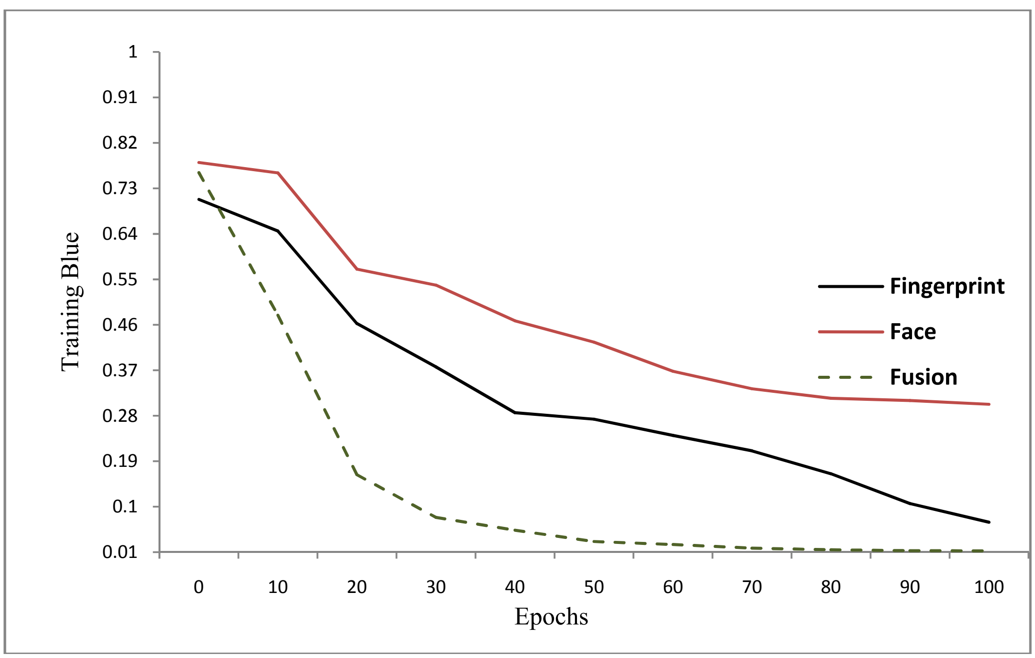

Fig. 8: Illustrates the idea of the research and summarizes the above table.

Conclusion:

The multimodal biometric system can improve the performance of the system .In this paper, the new insights and experimental results for face, fingerprint recognition have been presented. Where Gabor filters to global features extraction in face and fingerprint images are proposed. The simple feature level to fuse both modalities' features is used.

It was introduced and presented a new training technique which is based on liquid state machine with networks of randomly connected integrate-and-fire spiking neurons. The performance of an integrate-and-fire LSM was tested for two different modality face fingerprint.

The experimental results show that the combination face and fingerprint outperforms than using them individually. Finally, the proposed multimodal biometric system achieves a recognition accuracy of 98.73%. Furthermore the proposed method obtains a better recognition results than the other methods when only one modality is used.

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