Personal Identification by Fingerprints based on Gabor Filters

Youssef ELMIR [1], Zakaria ELBERRICHI [2], Réda ADJOUDJ [2],
Mohamed BENYETTOU [3]

[1] Department of Mathematics and Computer Sciences,
Faculty of Sciences and Engineer Sciences,
Colonel Ahmed Draya University, Adrar, Algeria
ysfbr@yahoo.fr
[2] EEDIS Laboratory, Department of computer sciences,
Djillali Liabes University, Sidi Bel Abbes, Algeria
elberrichi@gmail.com
adjreda@yahoo.fr
[3] LAMOSI Laboratory, Department of computer sciences,
Mohammed Boudiaf University of Sciences and Technology,
Oran, Algeria
med_benyettou@yahoo.fr

Abstract: This work is released in biometric field and has as goal, development of a full automatic fingerprint identification system using methods which have been tested in LAMOSI laboratory. Promising Results of first experiences using radial basis function neural network and support vector machine pushed us to continue the exploitation of new version of neural networks which is spike neural networks and to develop codification and recognition algorithms which are specifically associated to this system. In this context, works were consecrated on algorithm developing of the original image processing, minutiae and singular points localization; Gabor filters coding and testing these algorithms on well known databases such as: **FVC2004** databases & **FingerCell** database. Performance Evaluating has proved that spike neural network achieved a good recognition rate closer to rates achieved by other methods but in a very short time and this make it more useful in online applications.

Key words: Biometrics, Core and Delta points Detection, Gabor filters coding, Image processing, Spike Neural Networks, Support Vector Machine, Radial Basis Function Neural Network.

1 Introduction

Fingerprint-based identification is one of the most important biometric technologies which have drawn a substantial amount of attention recently [11].

Fingerprints are believed to be unique across individuals and across fingers of same individual. Even identical twins having similar DNA, are believed to have

different fingerprints [11]. A fingerprint is the pattern of ridges and valleys on the surface of a fingertip [9].

Fingerprint recognition can be categorized into identification and verification. Fingerprint identification is the process of determining which registered individual provides a given fingerprint. Fingerprint verification, on the other hand, is the process of accepting and rejecting the identity claim of a person using his fingerprint.

Fingerprint recognition can also be categorized into minutiae extraction based and spectral features of the image based.

All technologies of fingerprint recognition, identification and verification, minutiae extraction based and spectral features based, each has its own advantages and disadvantages and it may requires different treatments and techniques. The choice of witch technologies to use is application specific.

In the following sections, we present in detail our proposed algorithm of recognition using spike neural network. The principle of Fingerprint identification is presented in Section 2. Sections 3 and 4 present the problem statement and our proposed design for it, respectively. We give the algorithm used to codify fingerprint images using a bank of Gabor filters in section 5, the architecture of our spike neural network in section 6, The experimental results on the FVC2004 and FINGERCELL fingerprint databases, are presented in Section 7. Finally, conclusion is given in Section 8.

2   How fingerprint identification works

At the highest level, all fingerprint recognition systems contain two main modules *feature extraction* and *feature matching*. Feature extraction is the process that detects singular and all other minutiae points which are ridge ending and ridge bifurcation which differentiate one fingerprint from another which impart individuality to each fingerprint." (See Fig 1) from the original image that can later be used to represent each fingerprint. Feature matching involves the actual procedure to identify the unknown person by comparing extracted features from his/her fingerprint with the ones from a set of known persons. We will discuss each module in detail in later sections.
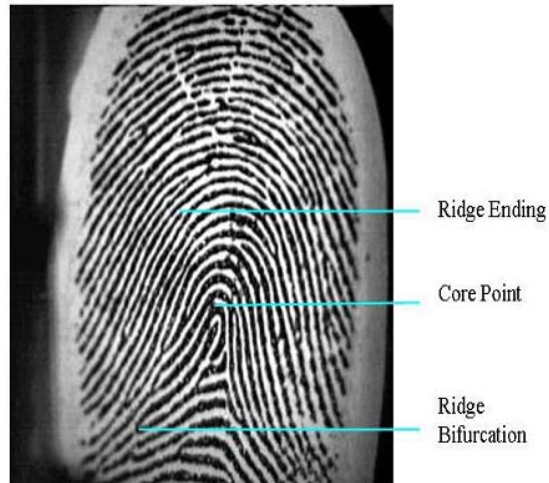
Fig. 1. *Ridge ending, core point and ridge bifurcation are shown [11].*

Although fingerprint authentication appears to be an easy authentication method in both how it is implemented and how it is used, there are some user influences that must be addressed.

Influence of several fingerprint image quality characteristics on the performance of the verification system [7].

The displaced, false or missing singular points [9].

Background noises will interfere with the user who is trying to authenticate to the device. The environment in which the user is authenticating to the device must be free of any major background noise [1].

3 Proposed design

The problem of fingerprint recognition is one of much broader topics in scientific and engineering so called pattern recognition. The goal of pattern recognition is to classify objects of interest into one of a number of categories or classes [1]. The objects of interest are generically called patterns and in our case are images of fingerprints matrix called vectors codes or fingercodes that are extracted from an input image using the techniques described in the later section. The classes here refer to individual person. Since the classification process in our case is applied on extracted features, it can be also referred to as feature matching.

This article demonstrates how fingerprint identification can be released with a spike neural network as matching process, but before the minutiae image of the fingerprint was converted into a vector code, also called fingercode, by using Gabor filter bank [6].

4 Problem statement

A spike neural network is to be designed and trained to recognize the fingercode of the databases that are actually used. An imaging system that converts each minutiae image obtained from a fingerprint image in fingercode or minutiae matrix code by using a bank of Gabor filters. The result is that each fingerprint image is represented as a vector of 256 real values. Finally, results obtained by spike neural network will be compared to those obtained by SVM and RBF.

5 Creating a fingercode

The following steps are observed to create the fingercode:
1. Preprocessing of the image (to remove noise) by window wise normalization, Histogram Equalization, low pass and median filtering [13].
2. Core point location using max concavity estimation [3].
3. Tessellation of circular region around the reference point.
4. Sector wise normalization followed by application of bank of Gabor filters which has following general form in the spatial domain [4].

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

$$x' = x\,\sin\theta + y\,\cos\theta. \tag{2}$$

$$y' = x\,\sin\theta - y\,\cos\theta. \tag{3}$$

Where f is the frequency of the sine plane wave along the direction θ (0, 45, 90 and 135 degrees) from the x-axis, $\delta_{x'}$ and $\delta_{y'}$ are the space constants of the Gaussian envelope along X' and Y' axes, respectively.
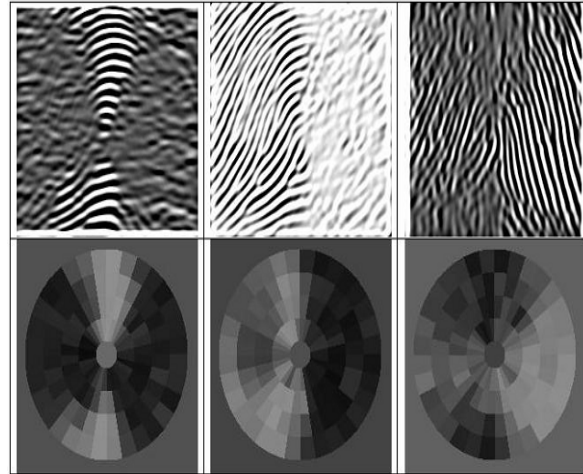
Fig. 2. Filtered images and their corresponding feature vectors for the orientations 0°, 5°. 22.5° and 45° are shown [11].

5. Finally feature code generation by obtaining standard deviation values of all the sectors, [4].

6 Fingerprint recognition

In less than few seconds, even on a database of hundreds of records, the matrix of pixels generated from an image of fingerprint is compared to previously enrolled ones to see if it matches any of them. The decision threshold is automatically adjusted for the size of the search database to ensure that no false matches occur even when huge numbers of matrixes of fingerprints are being compared with the live one. Some of the bits in a matrix signify if some data is corrupted (e.g. the image of fingerprint has degraded by noise), so that it does not influence the process, and only valid data is compared. Decision thresholds take account of the amount of data, and the matching operation compensates for any tilt of the image of fingerprint. A key advantage of fingerprint recognition is its ability to perform identification using a one-to-all search of a database, with no limitation on the number of fingerprint records and no requirement for a user first to claim an identity, for example with a card. For our method we use and experiment a recent neural network [5], called a spike neural network. The neural network is used for matching and performs recognition using a one-to-all search of a database.

6.1 Training with spike neural network

In tasks like pattern recognition, the performances of artificial networks are still poor when compared to humans. Using a go no-go categorization task in which human

subjects had to release a button when they detected an animal in a briefly flashed (20 ms) natural photograph [14], showed that the processing required in such a task could be performed in less than 150 ms. In order to reach high order cortical areas, the retinal information must go through at least 10 processing stages, and knowing the constraint of real neurons, (maximum firing rate usually under 100 spikes per seconds), they proposed that this processing was essentially based on a unidirectional flow of information in which, in any given layer, each neuron would rarely generate more than one spike. With one spike per neuron, codes based on neuron discharge rate are questioned. As an alternative to rate based neural codes, temporal coding is based on the relative order in which the spikes are produced is consistent with lateral inhibition in the first areas of the visual cortex. Spike neural network can use the latency or the relative latency of neuronal discharges - means their order of arrival and still attain high performances for image processing with only one spike per neuron. Furthermore, order coding is contrast independent and can be analyzed from a mathematical point of view. Spike neural network is designed for simulating very large networks of asynchronous spiking neurons. Neurons are simulated with a limited number of parameters that includes classic properties like the post-synaptic potential and threshold, but also more novel features like dendritic sensitivity. Spike neural network can be used to simulate networks with millions of neurons and hundreds of millions of synaptic weights. Optimization of computation time and the aim of a real time computation has been one of the driving forces behind the development of spike neural network [5]. There are some characteristics of spike neural network [5], [12]:

1. Perform image processing using biologically plausible network of neurons.
2. Simulate millions of integrate-and-fire neurons organized in retinotopical maps.
3. Connect these neuronal maps using projection files, and regroup common synaptic weights to save memory in order to be able to declare several hundreds of billions of synaptic connections.
4. Convert gray level images into lists of spikes (also spike neural network can perform a variety of preprocessing on the input images).
5. Implement a complex mechanism for projection between neuronal maps of different sizes.
6. Implement supervised learning.

For these characteristics, we create a new fingerprint recognition system which trained with spike neural network. When we tested rigorously the performances of spike neural network, it could compute roughly 20 million connections per second on a standard desktop computer (PC with speed of 3.0 GHz). This is sufficient to model a network of 400 000 neurons in real time, using a time step of 1 ms (assuming 40 connections per neuron, and an average firing rate of 1 spike per second, a value which is a reasonable estimate for the average firing rate of cortical neurons). Note that time resolution increases has virtually no effect on the computation time, and that adding a decay parameter to neurons adds roughly 30-40% to the computation time. Note that Number of synapses updated per second by spike neural network as a function of the number of neurons and the number of input synapses per neuron. Shared and individual weights indicate whether some neurons share same sets of

synaptic weights.

6.2 Architecture of spike neural network

To illustrate how Spike neural network can be used, we will describe a multiscale fingerprint recognition network which extends the fingerprint-localization model described by Van Rullen et al [12] and Delorme [5], and uses an architecture loosely based on the organization of the primate visual system. Input images are first analyzed by arrays of ON-center and OFF-center cells in the "retina» at three different spatial scales. These cells send spikes to neurons in the next layer which contains neurons tuned for 8 different orientations at each spatial scale. Lateral interactions between cells in this layer were used to improve selectivity, and are similar to those described by Zhaoping Li [15]. A weak shunting inhibition was also included to make the neurons sensitive to the order of activation of their inputs. A third layer in the network contains neurons selective for fingerprints at the three spatial scales. The connections between the level 2 orientation maps and these fingerprint-selective units were trained using a set of 200 images of fingerprints and a supervised learning procedure which attaches high weights to inputs which are systematically among the first to fire, and progressively smaller weights to later firing inputs. Finally, a fourth layer of neurons contains neurons which integrate the information at the three different spatial scales in the previous layer. The simulation is successful in that in the final map, the neurons fire if a fingerprint, at any scale, is present in the input image. The model is clearly not very realistic. For example, no attempt was made to model change in resolution with retinal eccentricity, but the architecture demonstrates how spike neural network can be used to create quite complex multilayer architectures involving large numbers of units, and it shows how different hypotheses could be tested and integrated easily in a biologically plausible neural network.

7 Experiment and test

7.1 Databases and datasets

To evaluate the performance of the proposed methods, it is necessary to dispose a database of fingerprints representing the purchasing system. Unfortunately these databases are not always available immediately.

It is available from the National Institute of Standards and Technology [10] bases of several thousand prints. These images were scanned from prints identity papers obtained by the traditional method of ink, they are very poor quality. To compare different methods of treating them, a competition was held to assess the performance of algorithms from the same images [8]. The databases are used openly and from three different sensors trade.

These databases are used in our case despite the acquisition systems used can rotate finger any angle. This is not the case in our system (assumption the existence of a guidance system).

Our system was tested with four databases of FVC2004 and FingerCell database.

To effectively represent the performance of the dataset's size should be large enough [2], but the number of images is large and the duration of the tests is very long. For practical reasons we are constrained to a bank of 152 images with 19 different sets of fingers, each dataset consisting of 8 images in the case of FVC2004 corresponding to various acquisitions of the same finger and in the case of FingerCell, a bank 190 images with the same number of different sets of fingers, but a different number of pictures related to various acquisitions of the same finger (10 images).

7.2 Results

Table 1 shows the results of recognition rate and performance of the proposed system.

Table 1. Recognition results on the person's fingerprint databases (of five data-sets) on a PC with speed of 3.0 GHz.

Database		SNN			RBF			SVM		
		Time for Train (ms)	Time for Test (ms)	Recognition Rate (%)	Time for Train (ms)	Time for Test (ms)	Recognition Rate (%)	Time for Train (ms)	Time for Test (ms)	Recognition Rate (%)
FVC 2004	DB1	19 219	91	73.68	2 265	71	63.15	32 094	1 379	68.42
	DB2	12 328	64	68.42	1 047	29	63.15	17 469	1 125	63.15
	DB3	14 109	71	84.21	2 891	107	68.42	18 297	906	73.68
	DB4	12 563	60	73.68	1 047	31	68.42	17 813	1 053	78.94
FingerCell		3 407	47	84.21	23 687	47	89.47	4 500	922	94.74

7.2 Resistance against Noise

The major obstacle in the fingerprint identification systems is the presence of noise in captured images of fingers during the training or test phase, which pushed us to study the reaction and performance of the system made against different noise levels applied to analyze its performance and see the error rates obtained for each noise level.

The noise used for the test system is a white noise, which is a matrix of random integer numbers distributed following a normal law of mean 0 and variance 1.

$$Noise \ = \ Randn \ \times \ Noise\_Level. \tag{4}$$

Where Randn is a function that gives the random integer number and Noise_Level is in the interval [0 ... 0.5] with a step of 0.1.

The performances of proposed systems are illustrated by the following graphs:
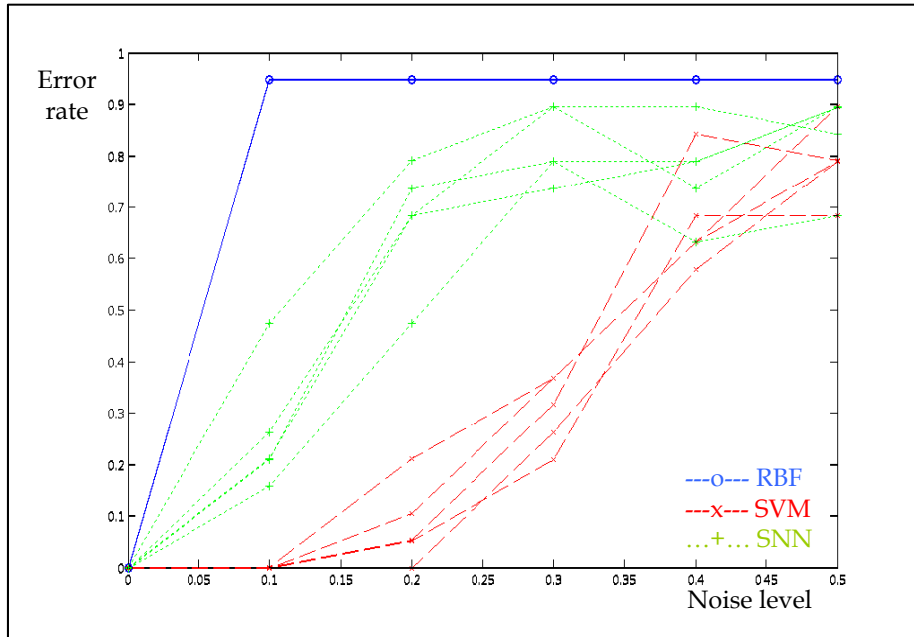

Fig. 2. Resistance of proposed systems against deferent level of noise.

In the figure above we can see that SVM resists against noise applied better than neuronal systems and that the graph of the spike neural network is very close to the graph of SVM unlike RBF that produces a significant number of errors from the beginning of test.

The error rates of the three methods are calculated at each noise level for the entire base. Performance graphs show that the SVM and the spike neural network methods are more resistant to noise than RBF which gives an outstanding error rates around noise level 0.1, while both spike neural network and SVM make low rate of error at this level, SVM maintain these rates until degree of noise (0.2), for against, spike neural network starts to produce a significant error rate in this noise level and after this value of noise level, rates of error produced by all methods begin to increase in a natural way with a significant degree of noise which can disrupt the even a human being recognition system.

8 Conclusion

Fingerprint recognition is a challenging problem and there is still a lot of work that needs to be done in this area. Over the past ten years, fingerprint recognition has

received substantial attention from researchers in biometrics, pattern recognition, image processing, and cognitive psychology communities. This common interest in fingerprint recognition technology among researchers working in diverse fields is motivated both by the remarkable ability to recognize people and by the increased attention being devoted to security applications.

Applications of fingerprint recognition can be found in security, tracking, multimedia, and entertainment domains. We have demonstrated how a fingerprint recognition system can be designed by a spike neural network, to capture the minutiae characteristics of fingerprint, to simulate the human visual system, although spike neural network designed as a tool for modeling biological neural networks, the level of performance obtained with spike neural network is such that in a variety of tasks, processing architectures developed using spike neural network can perform at least as well and in many cases substantially better than more conventional image processing and pattern recognition techniques. The levels of performance achieved by the human visual system are orders of magnitude better than even the most sophisticated artificial vision systems [5], [12]. By elucidating the computational principles which make this level of performance possible, it may well be possible not only to demonstrate the power of computational neuroscience as a paradigm for understanding biology, but may reveal the potential of the discipline in areas as diverse as machine vision and artificial intelligence.

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