# Neural Network-Based Approach for Detection of Liveness in Fingerprint Scanners

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***Abstract-*** *Fingerprints are the oldest and most widely used biometrics for personal identification. Unfortunately, it is usually possible to deceive automatic fingerprint identification systems by presenting a well-duplicated synthetic or dismembered finger. This paper introduces one method to provide fingerprint vitality authentication in order to solve this problem. Detection of a perspiration pattern over the fingertip skin identifies the vitality of a fingerprint. Mapping the two-dimensional fingerprint images into one-dimensional signals, two ensembles of measures, namely static and dynamic measures, are derived for classification. Static patterns as well as temporal changes in dielectric mosaic structure of the skin, caused by perspiration, demonstrate themselves in these signals. Using these measures, this algorithm quantifies the sweating pattern and makes a final decision about vitality of the fingerprint by a neural network trained by examples.*

**Keywords-** Fingerprints, Vitality, Biometrics, Neural networks, Capacitive scanners, Image processing.

## 1-Introduction

Personal identification is a very important issue in today's complex, mobile and electronically networked world. Among all biometrics, fingerprints are the oldest and most widely used [1]. Unfortunately, depending on the capturing technique, it is usually possible to fool automatic fingerprint identification systems by presenting a well-duplicated synthetic or dismembered finger. Some have suggested anti-spoofing measures based on physiologic features which may include measuring skin resistance, temperature, pulse-oximetry, electrocardiogram, and/or other physiological vitality indicators [2]. These measurements have the disadvantage of being bulky, expensive and/or easy to spoof. This paper introduces a new method for determination of the liveness or vitality of a finger. The corner stone of this new method is detection of (active) perspiration as a sign of life.

## 2-Background

Human skin houses 600 sweat glands per square inch and absorbs lipid-soluble substances [3,4]. Sweat, a dilute sodium chloride solution, is diffused on the surface of skin through small pores. Skin pores do not disappear, move, or spontaneously change over time. Our observations show that the pore-to-pore distance is approximately 0.5 mm over the fingertips. This agrees with Ashbaugh's model for pore frequency [5]. The skin can be modeled as a matrix of parallel resistors and capacitors. The electrical model of skin shows a mosaic structure because of perspiring pores, since sweat has such high dielectric constant and electrical conductivity compared to the (drier) lipids that build the outer layer of skin [6,7,8,9]. Generally speaking, the dielectric constant of sweat is around 30 times higher than the lipid [6]. This research uses a capacitive proximity sensor array scanner. Capacitance sensors are composed of a 2-D array of capacitors [10] exposed to direct fingertip contact by a thin but very tough and resistant dielectric (passivation) layer. Each sensor's measured capacitance is translated into a grayscale level in the corresponding bitmap image of the captured fingerprint through a special circuitry. If the skin in contact with the sensor is moist, then, because of very high dielectric constant of sweat, the underlying sensor will yield a much higher capacitance, resulting in a darker (saturated) spot on the captured image. This feature makes these scanners specifically suitable for detection of perspiration.

## 3- Methods and Materials

A Veridicom (Santa Clara, CA) FPS100 capacitive fingerprint scanner was used as the capturing device in this research. It was connected via USB port to a 233 MHz Pentium based personal computer. Software was provided with the fingerprint scanner for image capture. Matlab5 was used for all processing and computation. The training and test set includes 18 sets of fingerprint images from live individuals (IRB protocol HS # 14517), 18 from cadavers (IRB protocol HS # 14239), and 18 from spoofs. The eighteen spoof sets were developed from play dough using rubber-based casts.

## 4- Description of Physiologic Phenomenon

Inspection of live versus cadaver/spoof fingerprint scans produced the following observations:

1- In live fingers, perspiration starts from the pores. Typically the first fingerprint scan will look "patchy" due to this process and has formed the basis of our *static* approach for classification.

2- Second, the sweat diffuses along the ridges in time, making the semi-dry regions between the pores moister (darker in the image). Unless the skin is extremely dry, the pore region remains saturated while the moisture (sweat) spreads towards drier parts. This fact, captured by comparing two fingerprint images within 5 seconds, forms the basis of our *dynamic* approach (Figures 1 and 2).

3- The perspiration process does not occur in cadaver or spoof fingers.

As can be seen, the basis for our method is simple and straightforward. Live fingers, as opposed to cadaver or spoof, demonstrate a temporal change in moisture due to perspiration, and the fingerprint scanner is sensitive to this moisture. The challenge of an image processing algorithm is to quantify the sweating pattern.

Figure 1 Live fingerprint at t=0

Figure 2 Live fingerprint at t=5

## 5- The Algorithm

To quantify the perspiration phenomenon in the time sequence of images, an algorithm was developed to map a 2-dimensional fingerprint image to a "signal" which represents the gray level or moisture values along the ridges. The last image collected is used to determine the location of the ridges, since it usually has darker ridges and yields better quality. Below are the basic steps performed in the algorithm.

1- Capture: An important point here is that the finger should not be moisture-saturated initially. The basis for this algorithm is detection of perspiration. If the skin is already very moist, the scanned image will be detected as a temporally stable fingerprint (steady state). If the finger is in such a state, one can rub his/her finger against a piece of cloth, before the capturing begins. The first and last fingerprint images are captured 5 seconds apart, during which time perspiration occurs.

2- Pre-process: A program developed to clean up the image subtracts the permanent irregularities in the scanner by comparing it to a "blank" capture. It also removes the background static by discarding those pixels that change only within 2% of the "blank" scan. Next, a 3x3 median filter is applied here to cover the white pixels in the middle of the pores. This also smoothes the image further and eliminates "salt & pepper" noise, if any.

3- Convert to binary: Next a software module transforms the image to binary.

4- Contour extraction: By thinning the binary image of the last capture (until the ridges are one pixel wide, using a software routine) fingerprint ridge paths are determined. Y-junctions are removed using a simple 3x3 non-overlapping neighbor operation. The results of these three steps can be seen in Figure 3, where the extracted curves are superimposed on the original fingerprint for visualization. Curves shorter than 15 pixels are discarded since the nominal pore-to-pore distance is around 0.5 mm, spanning almost 10 pixels.

Figure 3 Fingerprint ridges as found by steps 2, 3, and 4 overlaid on the fingerprint image.

5- Static measure: The curves, which traverse through the middle of the ridges (Figure 3), cover varying gray levels in the fingerprint image. The peaks denote the moist locations and the valleys show the dryer regions, usually between each two pores. For live fingerprints, the peak-to-peak distance is around 10 pixels which is in accord with pore-to-pore distance (Figure 4). The variations in the cadaver/spoof fingerprint signal do not correspond to a specific periodicity because they do not have perspiring pores (Figures 5, 6). The main feature, which quantifies this, is the average Fourier transforms of the signal segments from the first capture where the energy related to the typical pore spacing is used. A 256-point FFT command is performed. Total energy is evaluated for a 8-24 pixel distance. This corresponds to a spatial frequency range is between 11 and 33. The procedure can be mathematically expressed as:

$$SM = \sum_{k=11}^{33} f(k)^2$$

where $$f(k) = \frac{\sum_{i=1}^{n} \left| \sum_{p=1}^{256} S_{1i}^{a}(p)\, e^{-j2\Pi(k-1)(p-1)/256} \right|}{n}$$

$$S_{1i}^{a} = S_{1i} - mean(S_{1i})$$

where n is total number of individual strings obtained in step 4 and $S_{1i}$ is the individual strings from the first image. This is an excellent measure, with its value being very low for cadaver and spoof compared to live (Figure 7).

6- Fingerprint signals: Individual strings are connected to form a long signal, which describes the gray levels of the contours passing through middle of the ridges, namely $C_1$ for first and $C_2$ for last capture. Figures 4, 5, and 6 are three (magnified) samples from portions of the signals extracted from a live, cadaver, and spoof fingerprint, respectively.

7- Dynamic Measures: The dynamic features are described below:

*Total swing ratio of first to last fingerprint signal:* According to our hypothesis, the fluctuation of the live fingerprint signal should be more in the first capture when we have moist pores and drier regions in between the pores (and so higher peaks and lower valleys) compared to last fingerprint signal where the sweat has diffused into drier regions (and there are less variations in gray level). The results are shown in Table 1. In mathematical terms, the first dynamic measure (DM1) is as follows:

$$DM\,1 = \frac{\sum_{i=1}^{m} \left| C_{1i} - C_{1\,i-1} \right|}{\sum_{i=1}^{m} \left| C_{2i} - C_{2\,i-1} \right|}$$

where $C_{1i}$ and $C_{2i}$ refer to the gray level signal points of the first and last capture, respectively, and m is equal the length of the ridge signal. Note m is the same for $C_1$ and $C_2$ (since the same mask was used for $C_1$ and $C_2$).

*Min/Max growth ratio of first to last fingerprint signal:* For the live fingerprint signal, the heights of the maximums do not increase as fast as the minimums (the perspiring pores are already saturated). So the average ratio of the maximum growth to minimum growth of first compared to last should be larger for the live fingerprint signal compared to cadaver and spoof. The results are shown in Table 1. In mathematical terms, dynamic measure 2 (DM2) is as follows:

$$DM\,2 = \frac{\sum_{j} (C_{2j}^{\min} - C_{1j}^{\min})}{\sum_{k} (C_{2k}^{\max} - C_{1k}^{\max})}$$

where $C_{1j}^{min}$ and $C_{2j}^{min}$ are the local minimums for the first and last scan, respectively, and $C_{1k}^{max}$ and $C_{2k}^{max}$ are the local maximums. Location of minimums and maximums were determined from the second scan and applied to both.

*Last-first fingerprint signal difference mean:* When the first ridge signal ($C_1$) is subtracted from the last ($C_2$), the difference for a finger with no life is less than a finger that is perspiring; quantifying a temporal changing pattern of moisture. This feature is helpful because there is a general darkening effect for cadaver fingers over time, which translates to a signal with a baseline shifting up while maintaining the same ac pattern. This baseline shift cancels out in the subtracting procedure. The results are shown in Table 1. In mathematical terms, dynamic measure 3 (DM3) is as follows:

$$DM3 = \frac{\sum_{i=1}^{m}(C_{2i} - C_{1i})}{m}$$

m, $C_{1i}$, and $C_{2i}$ are the same as in DM1.

*Percentage change of standard deviations of first and last fingerprint signals:* The last proposed measure in the dynamic ensemble is the percentage change in standard deviation of last and first fingerprint signals for each case. The rational behind it is similar to the others: if the fluctuation of the ridge signal is decreasing around the mean (the change typical for live fingerprint signal), the fourth dynamic measure (DM4) will increase. In mathematical terms,

$$DM4 = \frac{SD(C_1) - SD(C_2)}{SD(C_1)}$$

where SD is the standard deviation operator.

8- Classification: Classification can be performed based on each of the developed measures individually. However, a decision based on a combination of the static and four dynamic measures is able to give a much better classification, as explained in next section.

Table 1 Equal error rates.

| Measure | EER (Live vs. Spoof) | EER (Live vs. Cadaver) |
|---|---|---|
| SM | 11.11% | 5.56% |
| DM1 | 22.22% | 27.78% |
| DM2 | 11.11% | 22.22% |
| DM3 | 16.67% | 38.89% |
| DM4 | 22.22% | 27.78% |

## 6- Classification and Results

The results of each individual measure for classification of live versus cadaver/spoof in terms of equal error rate are given in Table 1. EER happens when FAR=FRR [11]. None of the developed features alone can separate live and cadaver/spoof fingerprints with 100% sensitivity and specificity (or no false acceptances and no false rejections). However, since the underlying mechanisms for static and dynamic measures are different, a combination of all these measures provides better precision than any of the individual measures. In this study, neural network is used for classification.

A back-propagation neural network (BPNN) is utilized in this work to separate live from cadaver/spoof fingerprints. For convenience of training, bipolar targets (+1, -1) were chosen to denote live and cadaver/spoof, respectively. Log-sigmoid was used for the hidden layer's transfer function. Linear and tan-sigmoid were tested for the output layer's transfer function with tan-sigmoid being the best. BPNN's five inputs consist of the static measure and four dynamic measures. For this implementation, two-thirds of the data was used for training and one-third for testing. The network is trained using as many iterations (epochs) as needed until the sum of squared error (SSE) criteria, set at 0.02 in this study, is met. When presented with the test inputs that it had never seen before, the BPNN classified all of the cases correctly (Table 2).

## 7- Discussion and Future Work

The interesting finding during this research was that vitality of fingerprints could be determined from a new non-invasive method, detection of perspiration, by observing the fingerprint for a few seconds. It means that systems can become "spoof-proof" just by a simple software upgrade. Because this algorithm

Table 2 Output of BPNN for test set.

| Case | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| Live | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 0.9999 | 1.0000 |
| Cadaver | -0.9950 | -0.9944 | -0.9890 | -0.9938 | -0.9852 | -0.9827 |
| Spoof | -0.9906 | -0.9949 | -0.9939 | -0.8404 | -0.9747 | -0.9852 |

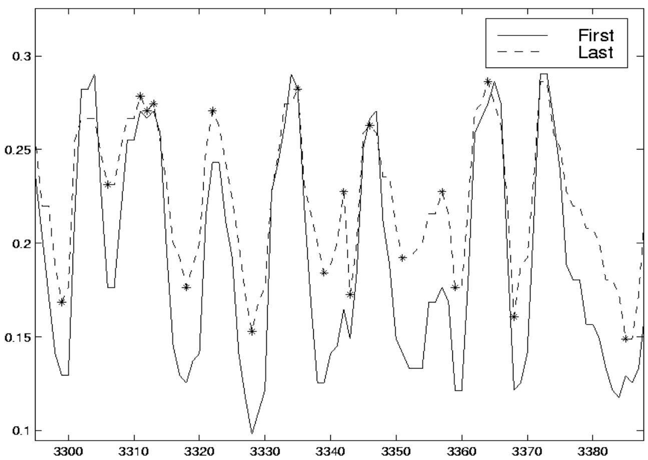


Figure 4 Portion of a live fingerprint signal. * denotes minimums and maximums.

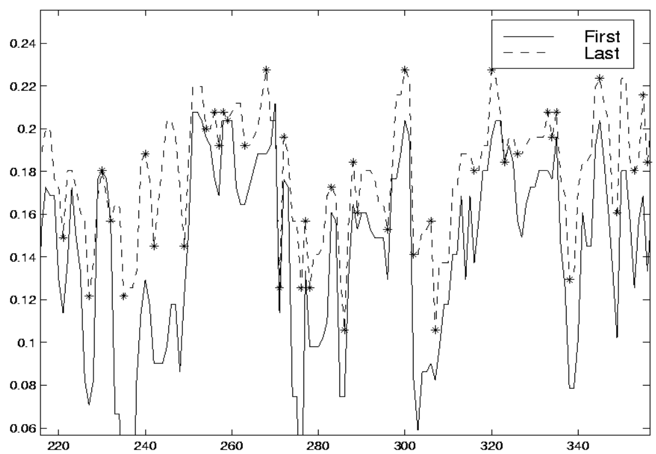


Figure 5 Portion of a cadaver fingerprint signal. * denotes minimums and maximums.

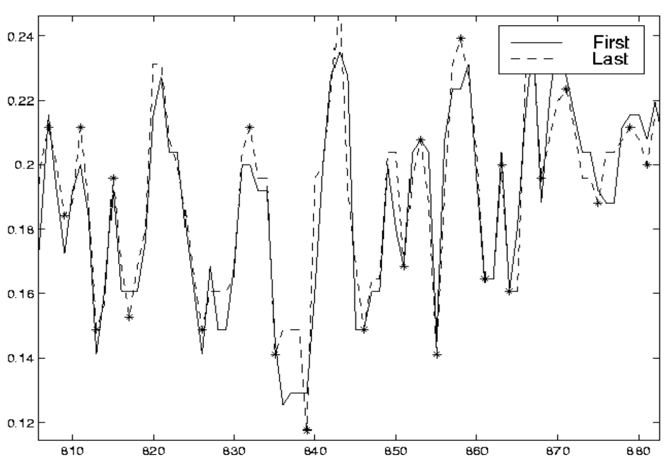


Figure 6 Portion of a spoof fingerprint signal. * denotes minimums and maximums.

expands upon the physiological phenomena of perspiration, it may experience difficulties in cases of perspiration disorders (finger too moist or dry) and other abnormal skin conditions. Nevertheless, one should note that these cases might also have problems when attempting to capture a usable fingerprint (because of abnormal moisture content). This is a subject to further investigation. Another issue is the orthogonality of the derived features. Specifically, the dynamic features may not independently quantify the event. Future work will be to investigate the overlap and reduce their number or extract a new set of features from the fingerprint signals. Another necessary improvement will be using a larger sample set both for training and for testing the algorithm. The sample set should include wider range of enrollees with different skin conditions in different climates and seasons. Another possible area of future work would be to decrease the time between the two captures, or to use more than two captures to derive more information. Tradeoffs between precision and speed of vitality verification will need to be addressed. More sophisticated algorithms may be harder to spoof utilizing features which further quantify sweat diffusion speed and dispersion dynamism. Finally, this algorithm and its future upgrades should be tested against spoofs which are made to simulate perspiration through artificial pores to evaluate the effort needed to spoof the algorithm.

As with all research, each study produces a new set of questions and potential improvements. In the area of security, complete security (without false rejects and accepts) will never be achieved permanently. The goal is to attempt to make spoofing of a system extremely difficult. This work introduces an additional requirement for fingerprint security through a successful method of vitality or liveness testing.

## 8- Conclusion

A new approach for detection of vitality through fingerprint examination in conjunction with capacitive scanners was introduced. This approach is based on detection of the sweating pattern from two consecutive fingerprints captured during 5 seconds. After mapping two-

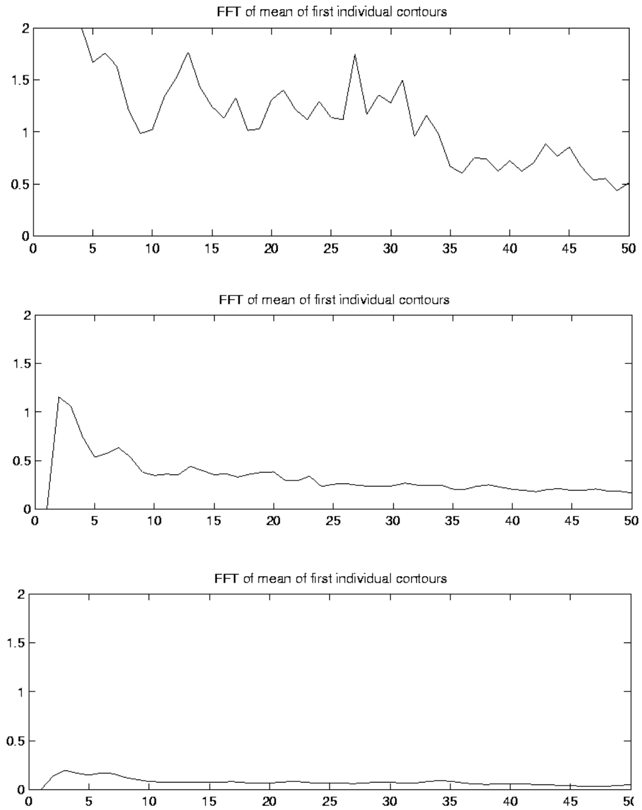

Figure 7 The average of the FFTs calculated from signal segments from live (top), spoof (middle) and cadaver (bottom) fingerprints.

dimensional fingerprints into one-dimensional signals, two ensembles of measures, namely static and dynamic measures, are extracted from them. Classification is performed using a back propagation neural network trained by the example fingerprints. It quantifies the sweating pattern and makes the final decision about vitality of the fingerprint. The method presented in here is a new measure for potential implementation in multi-modal biometrics systems. In addition to its accuracy (100% in this study), it is purely software based, so existing systems can be upgraded without any additional hardware.

This work has a US patent pending, provisional application submitted on October 7, 1999 [12].

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