A wavelet based approach to detecting liveness in fingerprint scanners

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ABSTRACT

In this work, a method to provide fingerprint vitality authentication, in order to improve vulnerability of fingerprint identification systems to spoofing is introduced. The method aims at detecting 'liveness' in fingerprint scanners by using the physiological phenomenon of perspiration. A wavelet based approach is used which concentrates on the changing coefficients using the zoom-in property of the wavelets. Multiresolution analysis and wavelet packet analysis are used to extract information from low frequency and high frequency content of the images respectively. Daubechies wavelet is designed and implemented to perform the wavelet analysis. A threshold is applied to the first difference of the information in all the sub-bands. The energy content of the changing coefficients is used as a quantified measure to perform the desired classification, as they reflect a perspiration pattern. A data set of approximately 30 live, 30 spoof, and 14 cadaver fingerprint images was divided with first half as a training data while the other half as the testing data. The proposed algorithm was applied to the training data set and was able to completely classify 'live' fingers from 'not live' fingers, thus providing a method for enhanced security and improved spoof protection.

Keywords: fingerprints, spoofing, liveness, wavelet analysis, multiresolution analysis, wavelet packet analysis

1. INTRODUCTION

Personal identification has gained immense importance in today's networked community. Traditional methodologies for personal identification such as photo identity cards and signatures are found to be not capable of providing sufficient security against well planned fraudulent attacks.[1] Fingerprints are considered as the oldest, most popular, and hence most widely used among various biometric identifiers. One of the negative implications of increased technological advancement is the ease with which, one can spoof into a biometric identification system. Fingerprint scanners are found to be vulnerable to different types of attacks from artificially prepared synthetic fingers, latent fingers, and, in worst case, dismembered fingers. Among various ways to improve fingerprint security, liveness detection has emerged where the system checks whether the source of input signal is a 'live' genuine finger or spoof finger. This helps the security system in differentiating 'live' fingers from 'not live' fingers. "Liveness" detection can be used as a supplementary security test in order to strengthen the security of the system under consideration.[2,3]

To make the test of "liveness" detection more accurate, further enhancements and improvisations in the techniques are desired. In this paper, a wavelet based method to detect "liveness" associated with perspiration changes in a time series of fingerprint images is proposed. In order to extract the desired information from the time series capture of images, maxima energy extraction, multiresolution analysis, and wavelet packet analysis are used. No hardware enhancements are needed as the proposed method is entirely software based.

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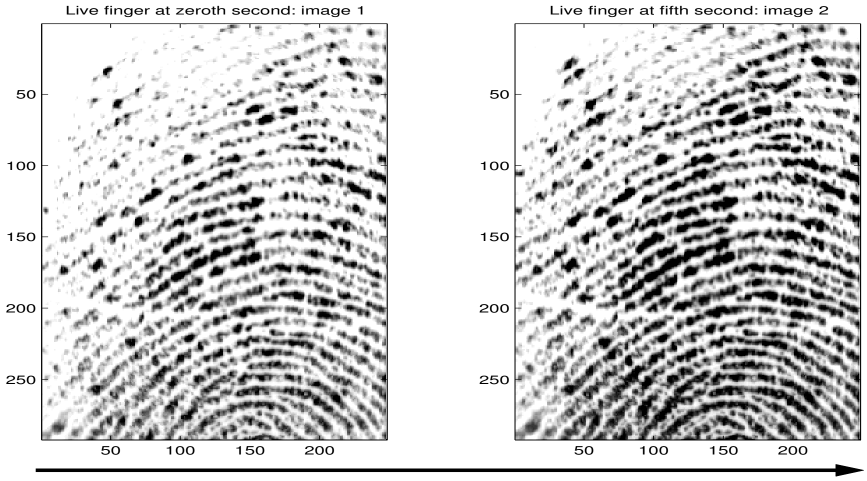

Figure 1. The fingerprints captured as a time sequence. The left figure is captured at zeroth second, while the right is captured after five seconds. Perspiration is observed as time progresses as it is a live finger.

1.1. Spoofing and Liveness

Fraudulent entry of an unauthorized person into fingerprint recognition system by using faux fingerprint sample is termed as 'spoofing'.[4] Recently different spoofing techniques have been reported, which include preparation of gummy fingers, use of latent fingerprints, fake fingers using moldable plastic, clay, play-doh, wax, and silicon.[4–7]

The ease with which fingerprint scanners can be spoofed is the driving force to check for "liveness" associated with fingerprint images. As the name suggests, the detection aims at making sure that the fingerprint sample introduced to the scanner has been provided by a live source.

Our laboratory has demonstrated that perspiration can be used as a measure of "liveness" detection for fingerprint matching systems.[4,8] Unlike cadaver or spoof fingers, live fingers demonstrate a distinctive spatial moisture pattern, when in physical contact with the capturing surface of the fingerprint scanner. This pattern evolves in time due to the physiological phenomenon of perspiration, and hence can be called 'perspiration pattern', as shown in Figure 1. Thus this pattern is nothing but the sweat spreading along fingerprint ridges as the time progresses. A signal processing-based method developed previously at our group has been developed and uses static and dynamic features derived from a signal isolated from the ridges with different classification methods like back propagation neural network, One R and discriminant analysis. This method is capable of producing classification rates in the range of 45% to 90% for all the scanners. Improvement in the classification rate is the motivation for this work.

1.2. Wavelet Analysis

For this particular study, the images are captured as a time sequence. The images captured at zeroth second and after five seconds, are used for analysis. The most significant information is carried by the singularities and sharp variation points of the image. Variation points can be analyzed as locations of contours in the image, which form the most important part of the feature extraction.[9] To quantify these features we first compute the wavelet transform of the images. The low frequency analysis is performed using 'multiresolution analysis', and high frequency content is analyzed using 'packet transform technique'.

Selection of mother wavelet is a critical issue in any wavelet based application. For this particular algorithm, Daubechies wavelet was selected as the mother wavelet. The filter was designed according to the 'cascade algorithm' given in.[10] The number of coefficients are selected to be 16. Only those roots of the periodic trigonometric polynomial are retained which lie inside the unit circle, to ensure minimum phase. By selecting maximum vanishing moments, it is possible to extract information even from the smoother parts of the images.

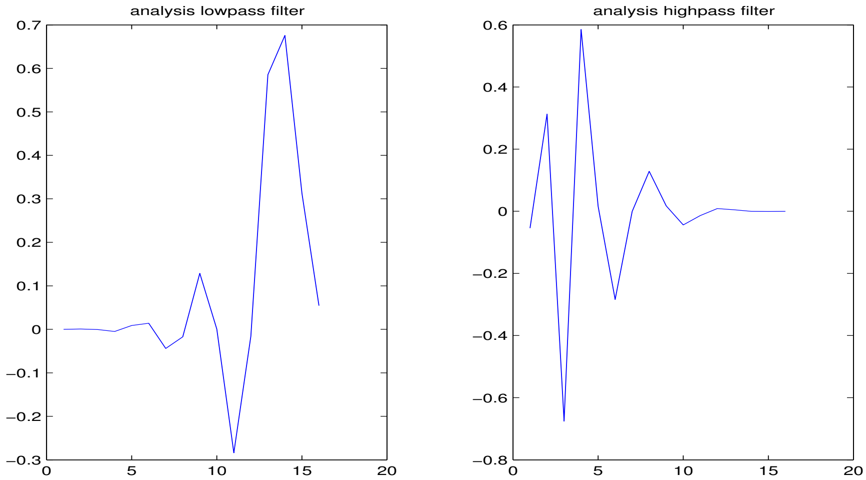

Figure 2. Daubechies analysis filters. The left figure shows low pass filter and the right figure shows high pass filter. The filters are designed for number of coefficients to be 16. X axis indicates the coefficient number, while the Y axis shows the value for that coefficient number. The filter is normalized so that sum of all the filter coefficients is equal to $\sqrt{2}$.

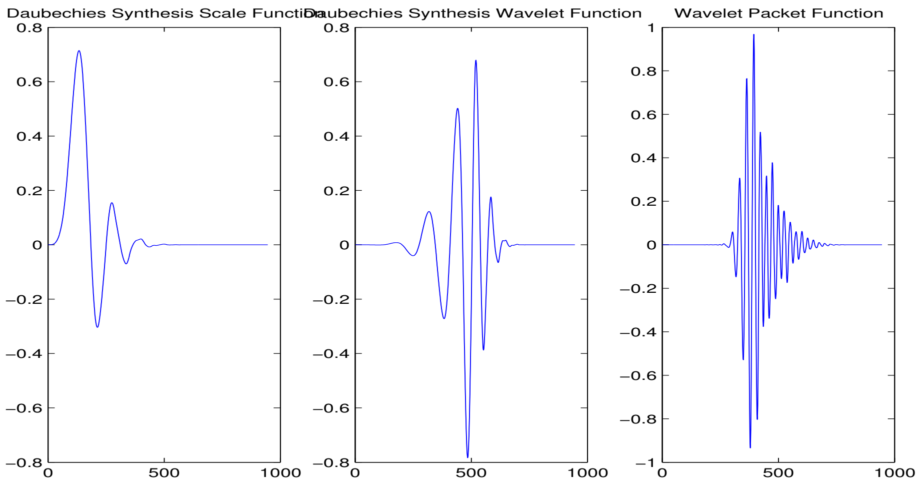

Figure 3. Left figure indicates Daubechies scale function (ϕ), middle figure indicates Daubechies wavelet function (ψ), and right figure shows the wavelet packet function. For all the figures the number of iterations are selected to be 5.

The main focus of the implementation is to construct compactly supported wavelets ψ.[10] The designed filters are shown in Figure (2). If the scaling function ϕ itself is chosen to have compact support, then it automatically ensures the compact support of wavelet ψ. Designed ϕ, ψ, and wavelet packet functions are shown in Figure (3). For entropy based wavelet packet expansion 'Coifman-Wickerhouser algorithm' is used.[11] For the "liveness" algorithm the coefficients from high frequency scale 3 were used from the resultant wavelet packet transform. Multiresolution analysis (MRA) leads naturally to a hierarchial and fast scheme for the computation of the wavelet coefficients of a given function. MRA was performed using the same filters in Figure (2). For the "liveness" algorithm the coefficients from low frequency scale 2 were selected for analysis from the MRA. More details are given in section 2.2.

2. ALGORITHM TO DETECT "LIVENESS"

The entire procedure can be divided into three parts. The first part includes pre-processing steps so as to prepare the data for the wavelet analysis. The second part is the actual wavelet analysis. Post processing steps are included in the third part.

The algorithm to detect "liveness" associated with fingerprint scanners:

1. Start

   Pre-Processing steps:

2. Sort and arrange data into training and testing data.
3. Input and convert images into a suitable format.
4. Remove noise using Median Filtering.
5. Equalize images using Histogram Equalization

   Wavelet Analysis:

6. Daubechies Wavelet Implementation
7. Wavelet Transform Implementation
8. Maxima Energy Extraction
9. Multiresolution Analysis
10. Wavelet Packet Analysis

    Post-Processing steps:

11. Sub-band Alignment
12. First difference and thresholding
13. Energy Distribution Analysis
14. Selection of Classification Threshold
15. Decide whether finger is 'live' or 'not live'.
16. To analyze another finger go to step 3.
17. If not stop.

The implementation is done using MATLAB(v6.5R13).

2.1. Pre-processing steps

Data previously collected in our lab is used to test the algorithm. This data set is sufficiently large, and diverse as far as age, sex, and ethnicity is concerned. This data set is comprised of different age groups (11 people between ages 20-30 years, 9 people between 30-40, 7 people between 40-50, and 6 people greater than 50), ethnicities (Asian-Indian, Caucasian, Middle Eastern), and approximately equal numbers of men and women. Most live subjects created a fingerprint cast for development of a spoof made from Play-Doh using method described in.[4,8] The data set consists of, in all, 69 fingerprints using Capacitive DC (Precise Biometrics, 100SC), 73 fingerprints using Electro-optical (Ethentica, USB2500), and 74 fingerprints using Optical (Secugen, FDU01), from live, spoof, and cadaver subjects. Enrollment (up to five tries) and verification (in at least one of six trials) was the criterion for inclusion in the study resulting in different totals for each device. The data set was divided into training and testing data sets with approximately equal number of fingerprints. The training

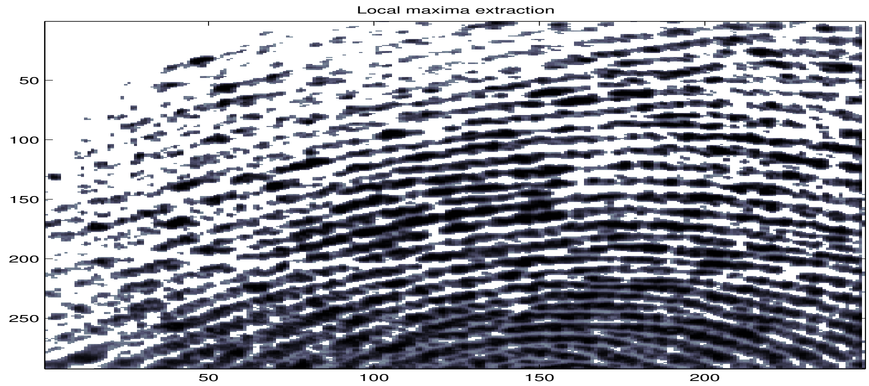

Figure 4. Maxima energy extraction. The figure shows a sample fingerprint image after retaining the most significant 10000 coefficients. This image is produced after making these coefficients undergo inverse transform.

data was used to test the algorithm and composed of 15 live, 15 spoof, 7 cadaver fingers for Secugen, 15 live, 15 spoof, 4 cadaver fingers for Precise Biometrics, and 15 live, 15 spoof, 6 cadaver fingers for Ethentica.

Two raw images captured by a biometric scanner at zeroth second and fifth second are selected for use in the algorithm. Before doing the actual wavelet analysis it is necessary to enhance the images. The major reasons are as follows:

- Captured images may not be clean because of the dust on the fingers or due to the latent finger impressions deposited on the scanner surface.
- The images could be of varying average contrast, due to the varying pressures at the time of the capture.
- The images could be too faint or too dark depending upon whether the finger is too dry or too sweaty.

Histogram equalization and contrast stretching are performed, to take into account the varying pressures at the time of captures as well as different initial moisture content of the skin. Median filter is implemented to remove sand and pepper type of noise, if any. Sharpening of the image follows, as the median filter is a smoothing filter.

2.2. Wavelet transform

After the images are enhanced, they are processed using Daubechies wavelet transform as described earlier.

2.2.1. Maxima energy extraction:

Maxima points of the wavelet transform undergo translation, rather than modification. These maxima energy points are capable of detecting sharp variation points, thus helping in characterizing patterns. So, the very first step performed after transforming the image is 'maxima energy extraction' for each scale. For this particular algorithm, the top 10000 coefficients are retained for each sub-band. This is shown in Figure (4).

2.2.2. Multiresolution analysis (MRA):

MRA helps in analyzing the low frequency content of the image. It simultaneously analyzes the image at different scales. For this study, the scale selected is 2. As the scale increases the image gets more and more blurred, eventually adding the low pass effect. For the varying scales, by selecting appropriate type of analysis filters, segmentation into horizontal, vertical, and diagonal directions is possible. The combination gives the image with all the details embedded, for that scale.

2.2.3. Wavelet packet analysis:

Wavelet packet analysis is utilized for high pass analysis. The best basis is searched by weighing the nodes of every branch of the basis tree vector individually. For the purpose of this algorithm, the scale selected for the wavelet packet transform is 3. For this algorithm, norm values are used to calculate the weights of the node, and thus to formulate the basis vector. The wavelet packet expansion is done as per Coifman-Wickerhouser algorithm.[11] Best basis is selected for the image captured at zeroth second, and the same basis vector is used for the image after fifth second. This is to have similar sub band division, in order to avoid any mis-match while taking the difference. The details are shown in Figure (5).

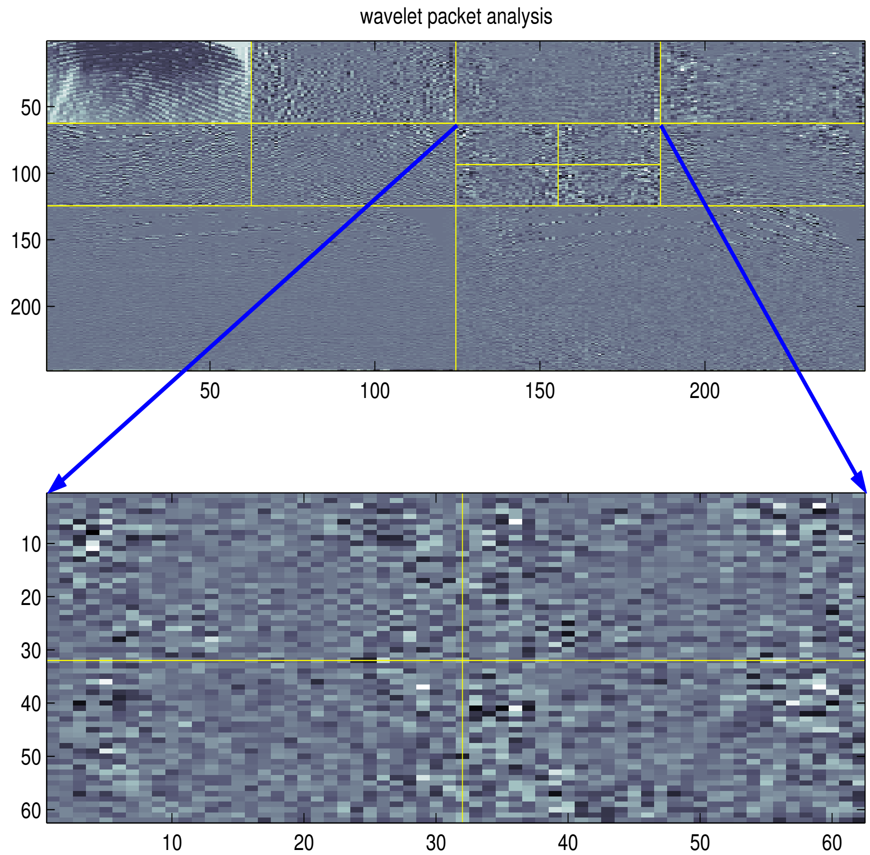

Figure 5. Wavelet packet transform. The scale selected is 3, and all the sub-bands are marked. Only high pass scale 3 sub-bands are retained for further analysis. Those are shown separately.

2.3. Post-processing

2.3.1. Sub band alignment:

Although this particular step takes very little effort as far as coding and analytical mathematics is concerned, this step is extremely essential. This alignment maintains the phase of the input signal throughout the process. To equate the lengths of the input and output sub band vectors either zero padding is implemented or alternate deletion is performed. This is performed while keeping the band energy maxima at the center.

This particular step is very important in case of Ethentica scanner, because the size of the captured images is 315×240, and so the chances of mis-matched sub bands are high. The images captured by the remaining scanners are 248×292 in dimension. The chances of mis-match are comparatively less.

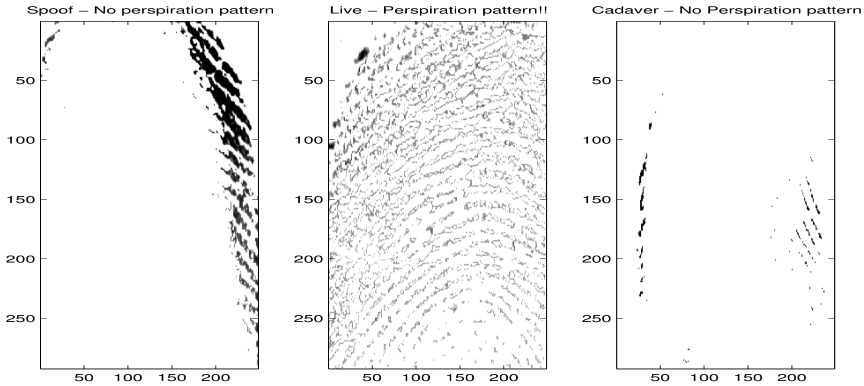

Figure 6. Perspiration patterns. The figures are spoof finger, live finger, and cadaver finger respectively, from left to right. As seen, perspiration pattern is observed only in case of 'live' finger. The perspiration pattern is obtained by adding individually processed sub bands.

2.3.2. Threshold selection:

Both the images, namely image captured at zeroth second and after five seconds are decomposed using the MRA scheme, followed by the wavelet packet scheme as described in section 2.2. Then, the first difference of the individual sub bands is taken, and all the outcomes are finally added to formulate the actual difference image. Most of the times the singularities are not very obvious in image, nor do they reflect in the wavelet coefficients. So, non-significant coefficients of the discrete wavelet transform are discarded and rest are enhanced. This process is called "thesholding".

A threshold value is used to decide a coefficient has experienced significant change. Each coefficient is retained if it changes more than 40% over 5 seconds, which, when transformed to spatial domain, represents 90 on the 8-bit scale. Coefficients which do not change more than 40% are discarded.

After processing the sub-bands separately, they are added, and inverse transformed to formulate the 'perspiration pattern'. These patterns for different types of fingers are shown in Figure (6). The perspiration pattern, enhanced and quantified by the algorithm described above, is observed only in 'live' fingers.

2.4. Energy Distribution Analysis

2.4.1. Energy Normalization:

The energy content of the difference image is retained if the image captured at zeroth second correspondingly has a non-zero value associated with it. This is very essential to avoid false energy increments in case of fingerprint spreading on the edges of the image as the time progresses.

Total energy associated with the changing coefficients, described in the previous section, normalized by total energy for the 5 second image, is used as the measure to decide "liveness" associated with each pair of images.

$$e\% = \left(\frac{\sum \text{energy of sub bands of the difference image after applying threshold}}{\sum \text{energy of sub bands of the image captured after five seconds}}\right) \times 100 \tag{1}$$

The training data set is used to determine the threshold value for each scanner. The results are shown in Figure (7).

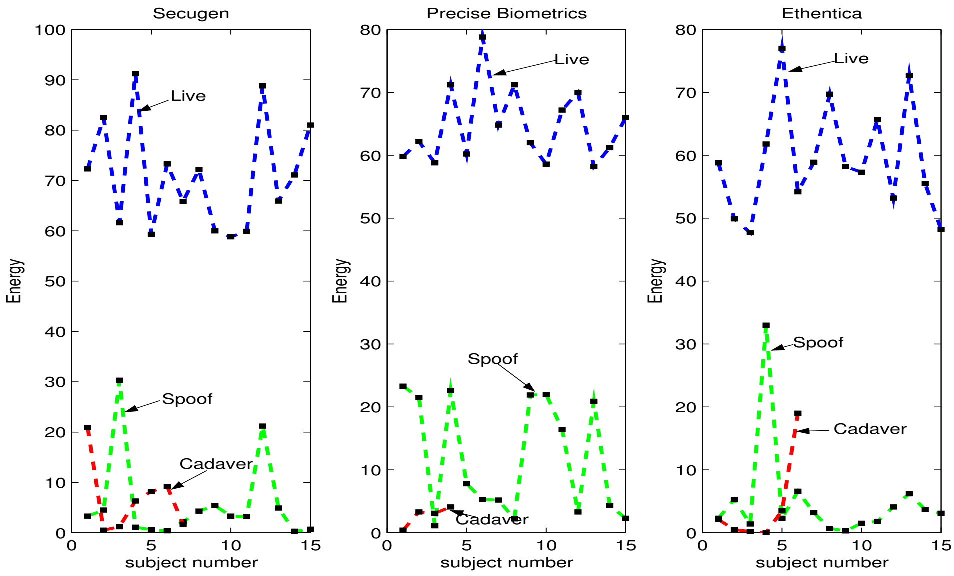

Figure 7. Training data set results. The graphs are for optical, capacitive DC, and opto-electrical scanners respectively, from left to right. Clear separation among energy distributions of 'live', and 'not live' fingers is obtained.

3. RESULTS AND DISCUSSION

Since there is no overlap between the energy content distributions of live and cadaver/spoof distribution, we can perfectly separate the two groups using a threshold that falls between the maximum of the cadaver/spoof distribution and the minimum of the live distribution. This is true for all three types of scanners. The following thresholds were chosen.

- **Threshold level of optical scanner = 44.55**
- **Threshold level of capacitive DC scanner = 40.75**
- **Threshold level of opto-electrical scanner = 31.6**

These thresholds will be evaluated on a separate test set.

The data collected for this particular study is at room temperature and at normal humidity conditions, from live subjects and from spoof and cadaver samples. Analyzing the perspiration changes as per the ambient conditions is beyond the scope of the work presented in this paper. In addition, it would strengthen the capability of the algorithm to do the job, if tested using wider and bigger data set, and for different other scanner technologies.

4. CONCLUSION

A wavelet based approach to detect "liveness" associated with the fingerprint scanners is presented. The approach is based on detection of 'perspiration pattern' from two successive fingerprints captured at zeroth second and after five seconds. It can be concluded that, the method presented in this paper *completely* classifies 'live' fingers from 'not live' fingers from training data set. This method is tested and found to produce desired results for three different types of scanner technologies, namely optical, opto-electrical and capacitive DC. The method is purely software based, and no hardware enhancements are required, and hence is economical.

Finally, no system is perfect or provides a complete solution. The algorithm presented in this paper is an effort to improve the robustness of the fingerprint recognition system.

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