

Comparison of ridge- and intensity-based perspiration liveness detection methods in fingerprint scanners

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ABSTRACT

Fingerprint scanners can be spoofed by fake fingers using moldable plastic, clay, Play-Doh, wax or gelatin. Liveness detection is an anti-spoofing method which can detect physiological signs of life from fingerprints to ensure only live fingers can be captured for enrollment or authentication. Our laboratory has demonstrated that the time-varying perspiration pattern can be used as a measure to detect liveness for fingerprint systems. Unlike spoof or cadaver fingers, live fingers have a distinctive spatial perspiration phenomenon both statically and dynamically. In this paper, a new intensity based approach is presented which quantifies the grey level differences using histogram distribution statistics and finds distinct differences between live and non-live fingerprint images. Based on these static and dynamic features, we generate the decision rules to perform liveness classification. These methods were tested on optical, capacitive DC and electro-optical scanners using a dataset of about 58 live fingerprints, 50 spoof (made from Play-Doh and Gelatin) and 25 cadaver fingerprints. The dataset was divided into three sets: training set, validation set and test set. The training set was used to generate the classification tree model while the best tree model was decided by the validation set. Finally, the test set was used to estimate the performance. The results are compared with the former ridge signal algorithm with new extracted features. The outcome shows that the intensity based approach and ridge signal approach can extract simple features which perform with excellent classification (about 90%~100%) for some scanners using a classification tree. The proposed liveness detection methods are purely software based, efficient and easy to be implemented for commercial use. Application of these methods can provide anti-spoofing protection for fingerprint scanners.

Keywords: biometrics; fingerprint scanners; liveness detection; histogram distribution analysis; classification tree

1. INTRODUCTION

Biometric systems are emerging technologies that enable the identification/verification of an individual based on physiological or behavioral characteristics. Fingerprint recognition is considered as the most widely used and efficient technique for biometric authentication. However, a fingerprint sensor system is subject to various threats like attacks at the sensor level using artificial or, in the worst case, dismembered fingers [1]. Previous work has shown it is possible to spoof a variety of fingerprint sensors with a well-duplicated synthetic finger, made from plastic, Play-Doh, or gelatin, or with dismembered finger [1, 2]. From a security and accountability perspective, there is an urgent need that a biometric system has the ability to detect spoof biometric samples. Liveness detection is an anti-spoofing method in a biometric system to ensure that only “real” fingerprints are capable of generating templates for enrollment, verification and identification [3].

Several different techniques have been suggested for liveness detection, such as measuring the skin resistance, temperature, pulse oximetry and ECG etc. The main problems of these methods are requiring extra hardware, bulky, expensive to implement and inconvenience to the user [1].

Our laboratory has demonstrated that the time-varying perspiration pattern in the fingerprint images can be used as a software-based measure to detect liveness. Unlike the spoof or cadaver fingers, live fingers have a distinctive spatial perspiration phenomenon both statically and dynamically. Based on this principle, a ridge signal algorithm and a wavelet algorithm have been developed to detect the perspiration pattern [4, 5]. These methods are capable of producing classification rates in the range of 90% ~100% for the three scanners tested. However, the processing speed is relatively slow due to the complicated image processing and wavelet algorithms. Therefore improvement of the speed with reasonable performance for fingerprint liveness is the motivation for this work. First, a new intensity- based approach is developed which extracts static and dynamic features which quantify the grey level differences between live and non-

live fingerprints images [8]. This method uses images captured immediately following placement on the fingerprint scanner (zero second) and two seconds after placement. Second, this method is compared to an improved ridge signal algorithm using new features and a new classification method.

2. INTENSITY BASED APPROACH

Figure 1 shows an example of typical live fingerprints (upper) and spoof fingerprints made from Play-Doh (middle) and gelatin (lower). As can be seen, the perspiration phenomenon is visible only in the live subject samples. An intensity-based approach quantifies the perspiration pattern using histogram distribution statistics and finds distinct differences between live and non-live images. Here we select the green square in the middle part of the fingerprint image as the processing area. In an image processing context, the histogram of an image normally refers to a histogram of the pixel intensity values. This histogram is a graph showing the number of pixels in an image at each different intensity value found in that image [7], as shown in Figure 2. For an 8-bit grayscale image there are 256 (0-255) different possible intensities, and so the histogram will graphically display 256 numbers (x-axis) showing the distribution of pixels (y-axis) among those grayscale values.

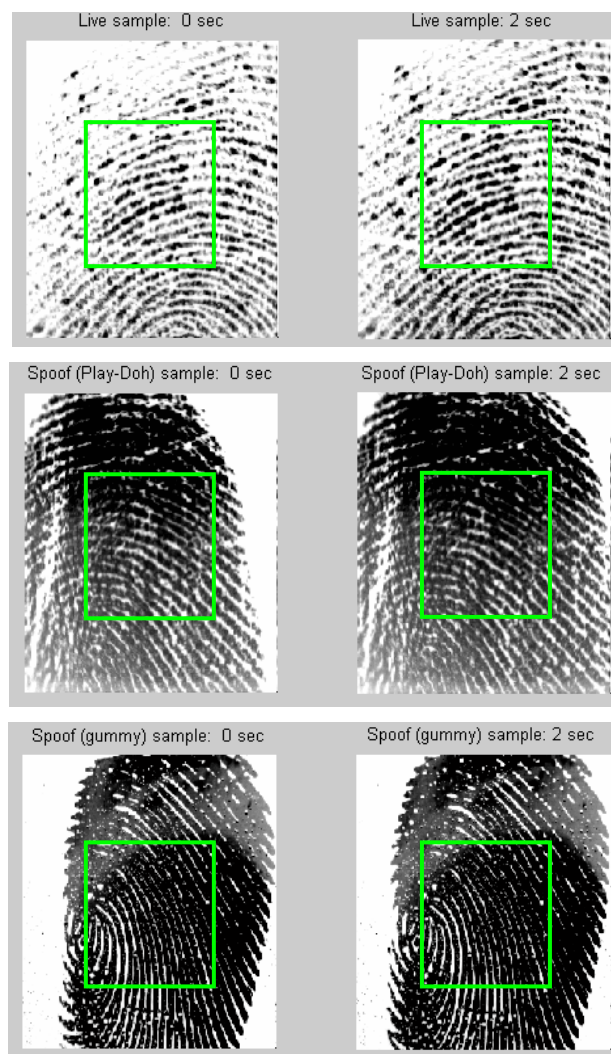


Fig. 1. Sample fingerprint images from live fingers (upper), spoof fingers made from Play-Doh (middle) and gummy fingers made from gelatin (lower) at 0 (left) and 2 (right) seconds

First, in live fingers, perspiration starts from the pores, either completely covering them or leaving the pore as a dry dot. Moisture has a darker grey level because sweat has a very high dielectric constant and electrical conductivity compared to the lipid-soluble substances absorbed by the outmost layer of the skin. Typically, live fingerprints look “patchy” due to this process compared to spoof and cadaver subjects. From the intensity distribution perspective, a majority of the intensity of live fingerprints are distributed in the white (> 250) grey level, while the intensity of the spoof and cadaver fingerprints images are distributed in the dark (< 150) grey level, as shown in Fig. 2. This forms the basis of our static features. Second, the perspiration diffuses along the ridges in time, making the semi-dry (white) regions between the pores moister and darker in the live image [4]. Therefore the live finger images have a larger difference in the histogram distribution between zero and two second compared to the spoof and cadaver subjects, which forms the basis of our dynamic features.

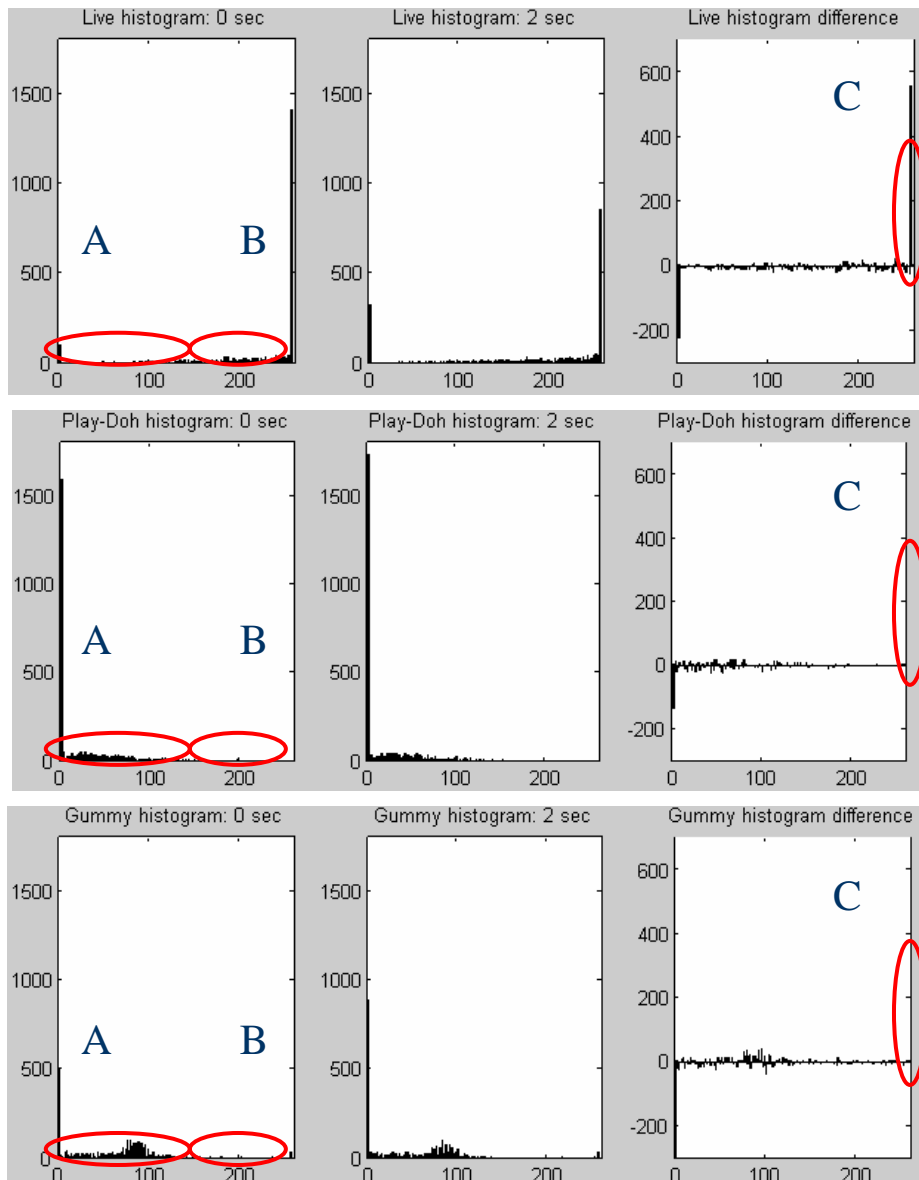


Fig. 2. Histogram distributions: 0 second (left), 2 seconds (middle) and their difference (right). The upper graphs are live sample, the middle graphs are the spoof sample made from Play-Doh and the lower graphs are gummy sample made from gelatin.

Based on the extracted static (one image) and dynamic features (two images at zero and 2 second), we generate the decision rules to perform liveness classification. The basic steps for this algorithm are listed as follows:

- Pre-process to remove the noise and normalize;
- Adaptively select an interesting square area in the middle part of the image while avoiding large scars;
- Perform histogram distribution analysis for both zero and two second images;
- Extract the static and dynamic features for efficient classification;
- Generate and determine the classification tree for each device type using the training and validation dataset;
- Test the classification tree using the testing data set.

To develop the liveness detection algorithm, different static and dynamic features were extracted for each scanner since intensity distributions varied across technologies. Here we take optical scanner (Secugen) as an example. In Figure 2, the upper is the histogram distribution of 0, 2 seconds and their difference (from left to right) for a typical live subject corresponding to Fig. 1 . The middle is the histogram distribution corresponding to a typical spoof subject made from Play-Doh. The lower is the histogram distribution corresponding to a typical gummy finger made from gelatin. Two static parameters from the zero second image and one dynamic parameter from the histogram difference are calculated as follows:

$$SM1 = \frac{B}{A} = \frac{\sum_{i=150}^{253} h1(i)}{\sum_{i=0}^{149} h1(i) + 0.1} \quad (1)$$

$$SM2 = B = \sum_{i=150}^{253} h1(i) \quad (2)$$

$$DMI = C = \sum_{i=254}^{255} |h1(i) - h2(i)| \quad (3)$$

Where $h1(i)$ and $h2(i)$ are the histogram distribution functions along the 256 gray levels at 0 second and 2 seconds, respectively.

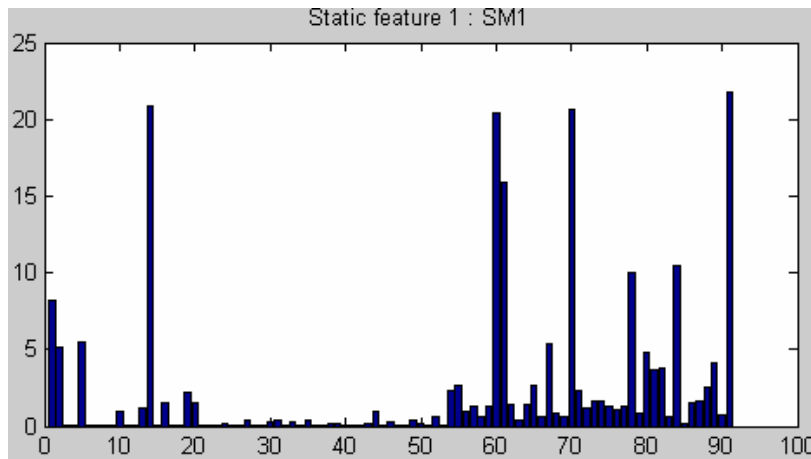


Fig. 3. Comparison of static feature SM1 (y-axis) across subjects (x-axis) (Cadaver: 1-19; Spoof: 20-53; Live: 54-91)

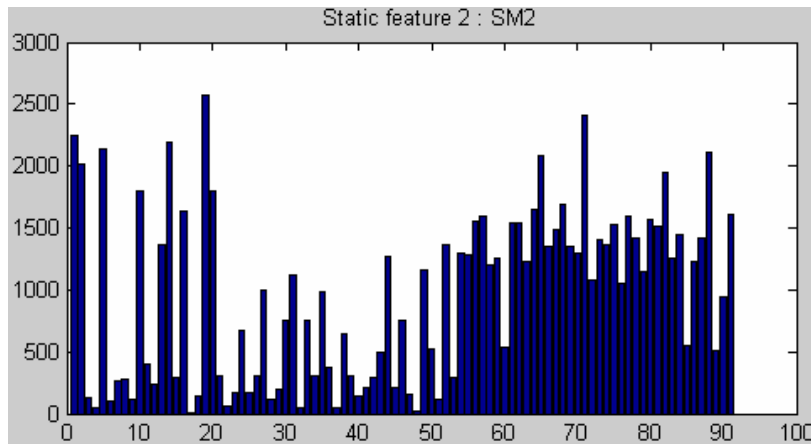


Fig. 4. Comparison of static feature SM2 (y-axis) across subjects (x-axis) (Cadaver: 1-19; Spoof: 20-53; Live: 54-91)

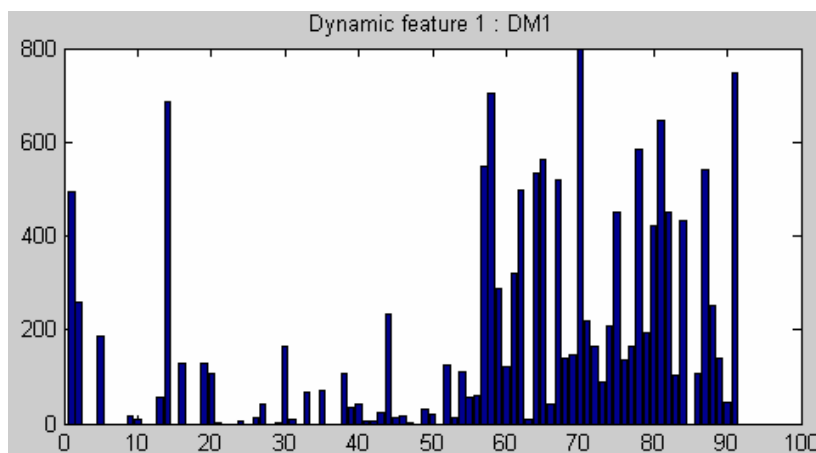


Fig. 5. Comparison of dynamic feature DM1 (y-axis) across subjects (x-axis) (Cadaver: 1-19; Spoof: 20-53; Live: 54-91)

As can be seen from results (Fig. 3, Fig. 4, Fig. 5) from the training and validation data, each of the three features provide separation between live and non-live fingerprints. According to our hypothesis, the live fingerprint looks patchy, which means a majority of intensities are distributed at the white region; the spoof and cadaver fingers look greyer and darker than the live fingers, which means a majority of the intensities are distributed at the dark and grey region. From the results of SM1 and SM2, we can see usually the value of cadaver and spoof fingers is lower than the live subjects except some special cadaver subjects, which conforms to our hypothesis. Also, the perspiration diffuses along the ridges over time, which makes the semi-dry image moister and darker. The results of DM1 in Fig. 5 confirm this point, which indicate that the live fingerprints have a larger dynamic difference between 0 and 2 seconds histograms than the spoof and cadaver fingerprints.

3. IMPROVEMENT TO THE RIDGE SIGNAL ALGORITHM

Previously, a ridge signal algorithm was developed which maps a 2-D fingerprint image into 1-D “signal” which represents the gray level values along the ridges. The last image collected (2 sec) is used to determine the location of the ridges, since it usually has darker ridges and better quality. Variations in gray levels correspond to variations in moisture both statically and dynamically. More details about this algorithm can be referenced in [4]. This algorithm extracts one static and six dynamic features and performs liveness classification using back-propagation neural network (BPNN). The static measure (SM) is the Fourier transform of the ridge signal (from the zero second) which quantify the “static”

variability in gray level along the ridges due to the pores and the presence of perspiration. The six dynamic features quantify the specific ongoing temporal changes (local maxima and minima) of the ridge signal intensity due to the active perspiration.

To increase the robustness and performance of this algorithm, two additional features are introduced in this paper. The first one is the Fourier transform of the ridge signal for the second image (SM2). In our recent research, it has been found that the Fourier energy difference of the last fingerprint signal is much more obvious than the first fingerprint signal.

The ridge curves cover the varying gray levels in the fingerprint image. For live fingerprints, the peak-to-peak distance is around 10 pixels, which is in accordance with the pore-to-pore distance [4]. The variations in the spoof/cadaver fingerprint signal do not correspond to a specific periodicity because they do not have evenly spaced perspiration pores. Here we extract another static feature which is the average Fourier transform of the signal segments from the second capture where the energy related to the typical pore spacing is used. It can be calculated as

$$SM2 = \sum_{k=11}^{33} f(k)^2, \quad (4)$$

where

$$f(k) = \frac{\sum_{i=1}^n \left| \sum_{p=1}^{256} S_{2i}^a(p) e^{-j2\pi(k-1)(p-1)/256} \right|}{n},$$

$$S_{2i}^a = S_{2i} - \text{mean}(S_{2i}),$$

in which n is the total number of individual strings and S_{2i} is the individual strings (i) from the second image.

The second feature is the number of the strings (SM3) in the 2 seconds fingerprint image, which is calculated from the fingerprint mask generated by morphological process. In our collection, the spoof fingerprints made from Play-Doh and non-live fingerprints from dismembered fingers have more strings than the live subjects because many ridges of the non-live fingerprints are not continuous. Fig. 6 shows one example about the ridges laid on live sample and corresponding spoof sample, in which the live fingerprint has 229 strings and the spoof fingerprint has 436 strings. Based on these original and new features, we improve the performance of this algorithm using classification tree method.

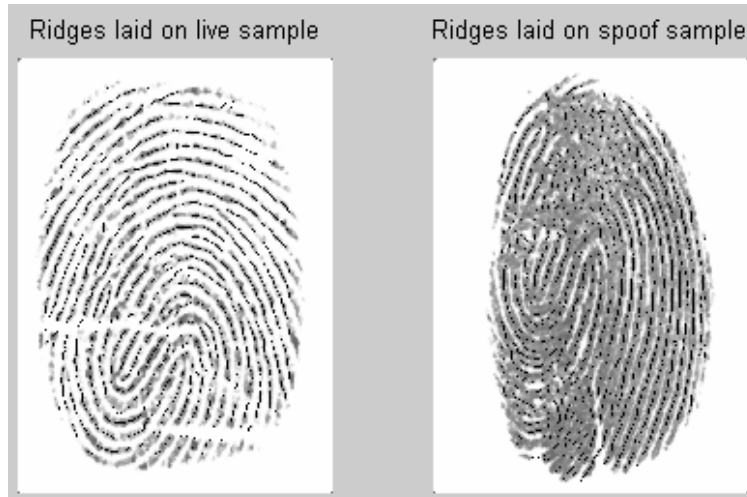


Fig. 6. Comparison of the number of strings between live (SM3=229) and spoof (SM3=436) samples

As can be seen from Fig. 7 and Fig. 8, these two new features can also work as measures (capacitive DC scanner as an example here) to discriminate between live and non-live fingerprints.

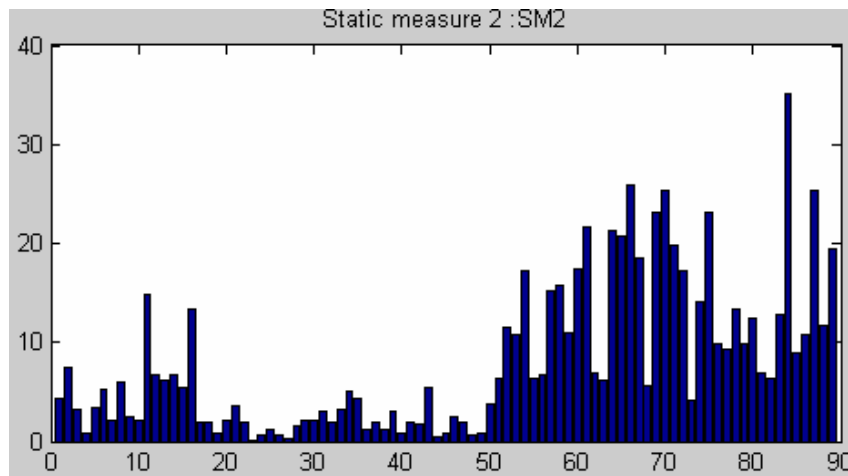


Fig. 7. Comparison of static feature SM2 (y-axis) across subjects (x-axis) (Cadaver: 1-16; Spoof: 17-51; Live: 52-89)

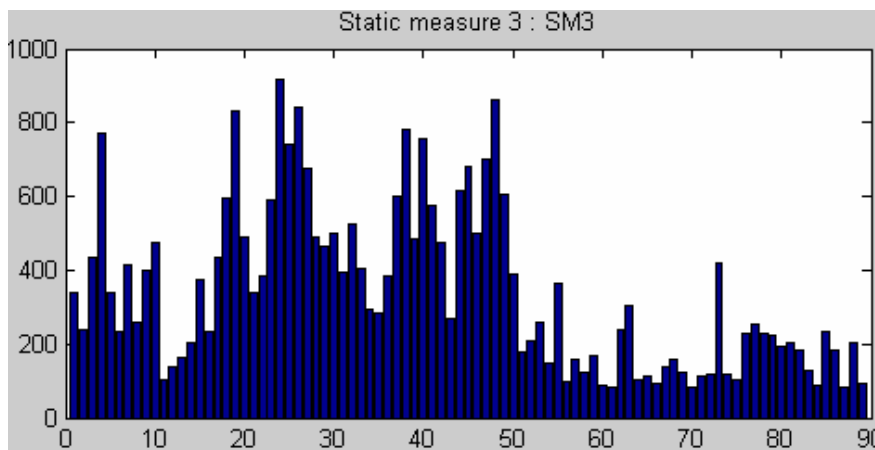


Fig. 8. Comparison of static feature SM3 (y-axis) across subjects (x-axis) (Cadaver: 1-16; Spoof: 17-51; Live: 52-89)

4. CLASSIFICATION METHODS

In this paper, classification trees are used to separate the spoof subjects from the live subjects. Unlike the neural network, classification trees derive a sequence of if-then-else rules using the training set in order to assign a class label to the input data. The user can see clearly about the decision rules to verify if the rules match their understanding about the classification. In our samples, while there are general trends, there are also some live fingers which may be very wet and change very little. In addition, some cadaver images change like live fingers but still have grey level differences which are different than live fingerprints. The classification tree works efficiently taking into consideration these situations. There are some commercial classification tree tools like CART, See 5 etc in use. In our case, an Excel tool developed by Dr. A. Saha was applied to generate the classification tree automatically [9]. The training and test data is randomly selected. Fig. 9 shows the classification tree selected for the optical scanner. For example, in this decision tree, the enrolled subject is classified as spoof if the first feature SM1 is less than 0.44984, which matches our investigation in the former discussion. Support means how many percent of the training data are supported by this rule and confidence means the confidence level about this specific decision rule.

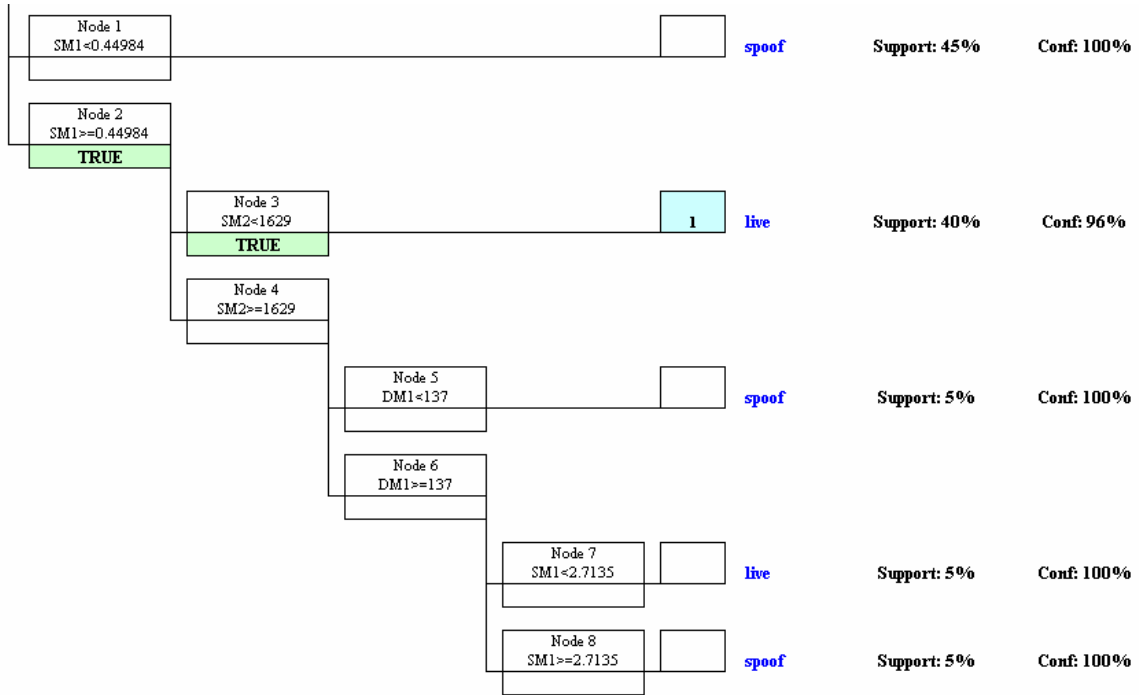


Fig. 9. Classification tree of the optical scanner

5. RESULTS AND DISCUSSION

Three types of fingerprint scanners were used to collect data in this study: capacitive DC (Precise Biometrics, 100sc), optical (Secugen, EyeD hamster model #HFDO1A) and electro-optical (Ethentica, USB2500). These systems were selected based on considerations of technology diversity, availability and flexibility of the SDK, and the ability to collect a time series of raw images. For each device, fingerprints images were collected from live, spoof and cadavers fingers. The dataset contains approximately 58 live (from different races, ages and balanced number of males and females), 50 spoof (40 made from Play-Doh and 10 made from gelatin) and 25 cadaver fingerprints. Table 1 summarizes the number of subjects used for each device and category. The images utilized in this paper are the first image and image from approximately two seconds after the start of time-series collection.

	Capacitive DC	Optical	Electro-optical
Live	58	58	55
Spoof	50	50	50
Cadaver	33	25	22

Table 1. Number of subjects used for each device and category

To evaluate our algorithms more objectively, the dataset is divided into training (4/9), validation (2/9) and test (1/3) datasets. The randomly selected training and validation data is used to generate and determine the classification tree. The decision tree which has the least FAR and FRR score is chosen as the one most likely perform well on the unseen test data.

Fig. 10 and 11 present the training and test classification rates for live and non-live fingerprints for each device using the intensity and ridge based approaches. The capacitive DC scanner demonstrates between 93.8-95% (non-live and live respectively) correct classification rate using the intensity method and 95-96.9% using the ridge method. The optical scanner demonstrates between 90-92% correct classification rate using the intensity method and 95-96% using the ridge method. Last, the electro-optical scanner has a lower classification rate which demonstrates between 76-88.9% correct classification rate using the intensity method and 77.8-88% using the ridge method, compared to the former two technologies. The reason why the capacitive DC and optical scanner have a better liveness classification rate is because these technologies are sensitive to the high dielectric constant of perspiration and the perspiration change pattern in 2 seconds.

Compared to the ridge based approach, the intensity based approach has a little lower correct classification rate (still above 90% in some scanners). However, it has a much faster classification speed (0.31s using Matlab7.0.1, Intel® Pentium® 4 CPU 2.8GHz, 1.11G RAM) than the ridge-based algorithm (6.5s) because it does not apply complicated image processing techniques.

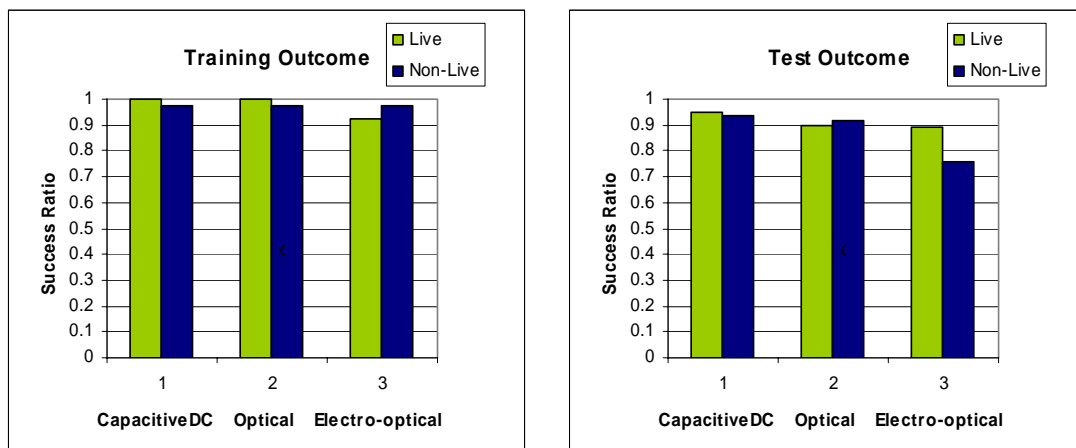


Fig. 10. Classification outcome of intensity based approach

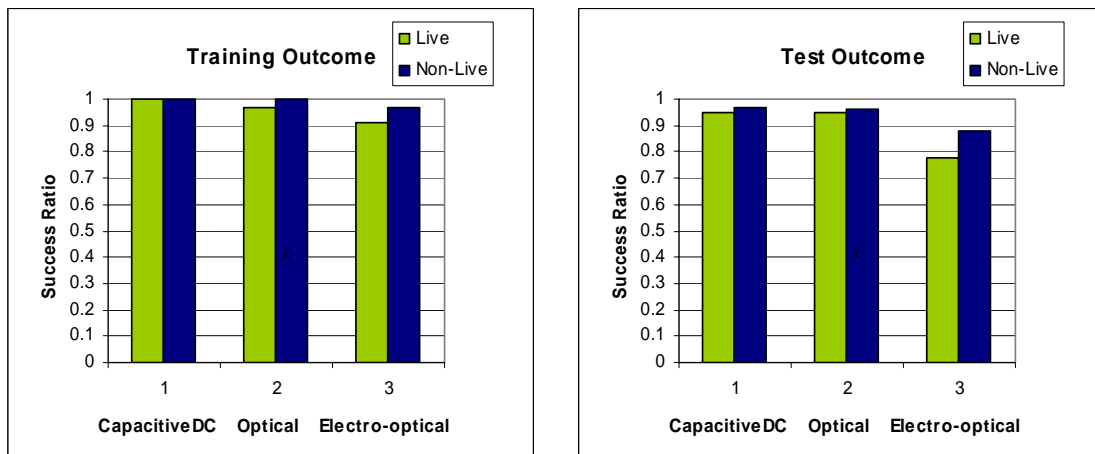


Fig. 11. Classification outcome of ridge based approach

Here we should note that both the intensity based approach and ridge signal algorithm are based on the gray level differences over time seen in spoof/cadaver images as compared to live images. The intensity-based approach quantifies these differences globally, while the ridge signal algorithm quantifies them along the ridges (locally). Grey level differences are specific to the type of spoof images we collected. Other spoof materials will need to be explored as they will have different gray level histograms. Also because the perspiration process are somewhat different between

different subjects and also depend on the initial moisture levels of the skin, a much larger test set is needed including subjects with different skin conditions in different climates and seasons as well as a more diverse background.

To further improve the intensity based approach, we are investigating automatic selection of the processing region which has the most prominent perspiration phenomenon. The perspiration pattern appears to behave more evidently in the outer edge part of the fingerprint image than the currently used middle part. Also our ongoing study is to investigate methods to detect liveness using one image to improve the classification speed. In addition, many of spoof images in our study were smudged. The intensity-based algorithm capitalizes on this feature. Live fingerprints which are excessively smudged might be detected as spoof. In most cases, a brief swipe on the subject's clothes would alleviate this problem. More testing will need to be performed for spoof images which may be less smudged and/or may imitate the perspiration pattern.

6. CONCLUSION

An intensity-based approach and improvement of the ridge signal algorithm using classification tree method are proposed to detect liveness for fingerprint scanners. The outcome shows that these methods based on perspiration phenomenon can extract simple features which perform good classification using classification tree. The proposed liveness detection methods are purely software based, efficient and easy to be implemented for commercial use. Application of these methods can provide anti-spoofing protection for fingerprint scanners.

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