World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:1, No:4, 2007

Aliveness Detection of Fingerprints using Multiple Static Features

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***Abstract*—**Fake finger submission attack is a major problem in fingerprint recognition systems. In this paper, we introduce an aliveness detection method based on multiple static features, which derived from a single fingerprint image. The static features are comprised of individual pore spacing, residual noise and several first order statistics. Specifically, correlation filter is adopted to address individual pore spacing. The multiple static features are useful to reflect the physiological and statistical characteristics of live and fake fingerprint. The classification can be made by calculating the liveness scores from each feature and fusing the scores through a classifier. In our dataset, we compare nine classifiers and the best classification rate at 85% is attained by using a Reduced Multivariate Polynomial classifier. Our approach is faster and more convenient for aliveness check for field applications.

***Keywords*—**Aliveness detection, Fingerprint recognition, individual pore spacing, multiple static features, residual noise.

I. Introduction

FINGERPRINT recognition systems are widely used in biometrics for person authentication because of their distinguished accuracy and efficiency compared to other biometrics. And they also have a great potential to be adopted in a wide range of forensic, government and commercial applications [1]. In spite of their numerous advantages, the systems are vulnerable to some attacks, which can decrease their security level. Ratha *et al.* [2] analyzed these possible attacks and grouped them into eight classes. Among these attacks, fake finger submission to the sensor is demonstrated by several researchers. Matsumoto *et al.* [3] showed some experimental results about attacking 11 different fingerprint recognition systems with gummy (gelatin) fingers. It was found that the gummy fingers could be enrolled in all of the 11 systems, and they were accepted with a probability of 68% - 100%. To solve this problem, several researchers suggested anti-spoofing methods by using dedicated hardware to acquire life signs of users. For example, temperature, pulse oximetry, ECG (electrocardiogram) and etc [4]. These approaches make a system becomes bulky and expensive. Furthermore, they lead to the inconvenience to users. On the other hand, aliveness detection methods based on using sole images have been proposed. For these techniques, the features used can be classified into static features from a single image and dynamic features from sequential images. Nowadays, there are mainly two dynamic features are extensively researched. Derakhshani *et al.* [5] showed that the perspiration patterns were observed only in live finger. The patterns were extracted from image sequences (from 0 to 5 seconds). Antonelli *et al.* [6] proposed a method using finger skin elasticity. They captured sequential fingerprint images when a user rotates his finger on a sensor and calculate the *DistortionCode* in each block of image. Both methods require users' cooperation such as keeping their fingers on a sensor for a few seconds or rotating their fingers on a sensor according to the guidance of the system. The methods may need high frame rate sensors for good performance. These requirements may be cumbersome for some users and not be suitable to some applications. Hence some researchers suggested several static measures. Derakhshani *et al.* [5] suggested using pore frequency of fingerprint as a static feature. Moon *et al.* [7] detected fake fingers by using image coarseness in digital camera acquired images. Abhyankar *et al.* [8] classified fake finger with image statistical properties. Though these techniques are convenient to the users, in terms of the classification performance is just marginal. Based on the above considerations, users' convenience, time saving and performance, we introduce a novel multiple static feature based aliveness detection method. Three static features including individual pore spacing, residual noise and first order statistics of fingerprint image are used. And these features are fused in score level by using Reduced Multivariate Polynomial (RM) classifier. The rest of this paper is organized as follows: we compare and describe static features in the following section. Section 3 presents our proposed method and feature analysis. Section 4 reports the experimental results. Conclusions are shown in section 5.

Manuscript received May 10, 2007. This work was supported by the Korea Science and Engineering Foundation (KOSEF) through Biometrics Engineering Research Center at Yonsei University.

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II. Static Features

A. Individual Pore Spacing

Pores are the small openings on the surface of fingerprint ridges formed by the duct of sweat glands [9]. The width of pores varies from 88 to 200 μm and their density is approximately 5 per mm^2 [10]. In addition, extensive researches show that pore patterns are unique to each individual.

And pore to pore distance is different from a person to another person, and varies depending upon the location in the finger [11]. Fig. 1 shows the photographical examples of pores. Also, by using the high resolution fingerprint sensor (over 1000dpi), we can capture the location of pores in detail (See Fig. 2)

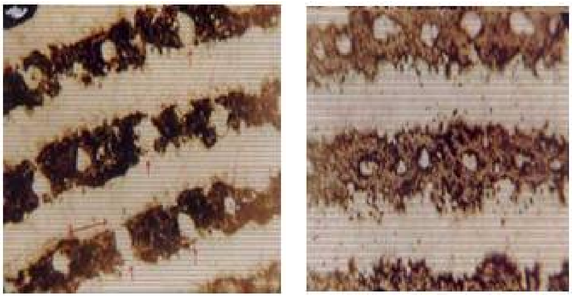

Fig. 1 The photo-micrograph examples of pores [11]

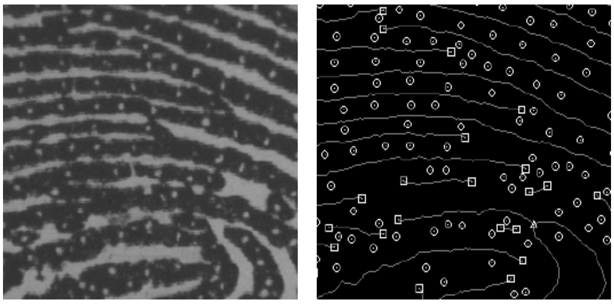

Fig. 2 The fingerprint image with 1000 dpi sensor [12]

Derakhahani et al. [5] analyzed the periodicity of sweat pores along the ridge. Their algorithm transforms a 2-dimensional fingerprint image into a 1-dimensional signal which represents the gray-level value along the ridge (called ridge signal). Fast Fourier Transform (FFT) is used to analyze the gray value variability due to the occurrence of pores. The total energy of ridge signal is then calculated between 11-33 FFT points. The live and fake fingerprint images are classified by thresholding the energy. However, due to the individual characteristics of pore periodicity, it is insufficient to discriminate a live finger from a fake one by using a simple threshold value. Hence, we analyze both the frequency shapes and powers of ridge signals of each person. Fig. 3 shows the individual properties of pore frequency from two persons.

To consider individual properties, the correlation filter which can reveal the characteristics of power spectrums of images is applied [13]. Specific explanation will be presented in section 3.A.

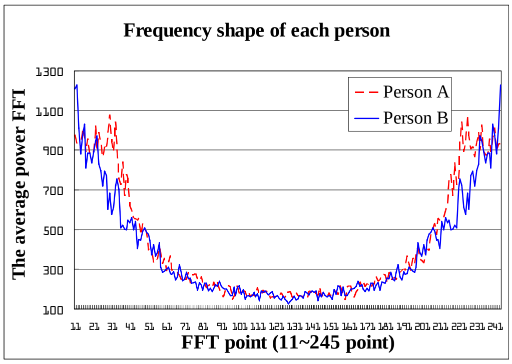

Fig. 3 Different frequency characteristic of each person

B. Noise of Fingerprint Image

Basically the materials that form a fake finger such as silicone and gelatin are different from the composition of skin. In addition, when making finger molds and fake fingers, there are a lot of variations according to various factors such as materials, weather conditions and expertness of manufacturer. In live finger, there are also variations according to skin condition and environmental changes. The variations, in making a fake finger, cause the coarseness of the fake finger surface to be treated as noise components in an image. Therefore noise of fingerprint image can be an important factor in aliveness detection. Moon *et al.* [7] detected a fake fingerprint by utilizing the texture coarseness of an image. They indicated that the surface of a fake finger is generally coarser than a live finger. The coarseness was measured through the standard deviation of noise residue in an image. Noise residue is calculated by the difference between an original and de-noised image. *Dmey wavelet* was used for de-noising. Instead of using conventional touch-based sensor, they used a high resolution digital camera (over 1000dpi). Hence, this method cannot be used directly in touch-based sensors.

In touch-based sensors, the coarseness of the fingerprint surface generally disappears because the sensors generate an image through the contact of a finger surface. The contact of a live finger depends on skin humidity of a finger [14]. When a finger is dry, uniform contact does not occur with the sensor surface. Thus it can generate an image which has large high frequency components or noises. On the other hand, if a gelatin- finger is dry, the softness of the material can be lost; it is difficult to make a contact with a sensor. Therefore the gelatin- finger must conserve a certain amount of moisture, so that it appears similar to a wet fingerprint image. Hence the residual noise of a gelatin-finger is smaller than a dry finger. Generally speaking, the pore periodicity of a live finger can be detected well when finger is dry. Therefore we can classify live and fake finger through the amount of residual noise. Fig. 4 shows the examples of original and noise residual images of live and fake fingerprint.

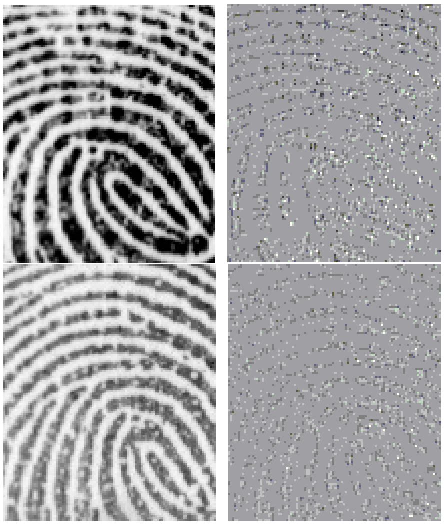

Fig. 4 The example of original and noise residual images of live (top) and fake (bottom)

C. *Statistics of Fingerprint Image*

A. Abhyankar *et al*. [8] detected a fake finger by using the first and second order image statistics. The first order image statistics are the commonly used features in texture analysis. They were supported by histogram changes [8]. There are 7 first order statistics such as energy, entropy, median, variance, skewness, kurtosis and coefficient of variations. And they detect a fake finger through the difference of these statistical properties. We apply these first order statistics as our static features.

III. Feature Analysis and Fusion

Fig. 5 shows the flowchart of our proposed method. The static features used include individual pore spacing (feature 1), the noise and the first order statistics of fingerprint images (feature 2 and 3). Especially, individual pore spacing is analyzed by using the proposed correlation filter method. The classification can be made by calculating the liveness scores from each feature and fusing the scores through a classifier. Finally, we decide whether a finger is live or fake.

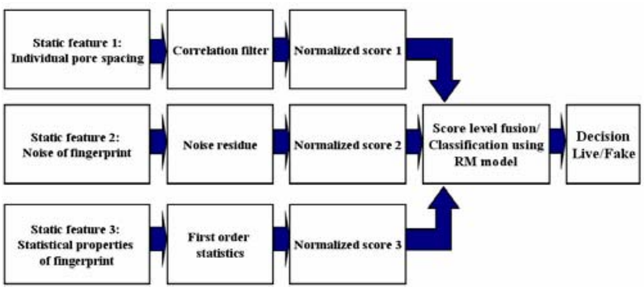

Fig. 5 Flowchart of proposed method

A. *Analysis of Individual Pore Spacing*

As discussed in section 2.A, periodicity of pores in ridge is shown to be personal. Therefore the related frequency information of pores is different to each identity. The individual properties of pore periodicity are shown by the envelope of power spectrum of ridge signal. Considering the shape of frequency response, the correlation filter generated from one's fingerprint images can have similarity to his other fingerprint images. Consequently we can detect a fake fingerprint image because the characteristics of pore information would not be similar to live one. The idea of fake finger detection using a correlation filter is illustrated in Fig. 6.

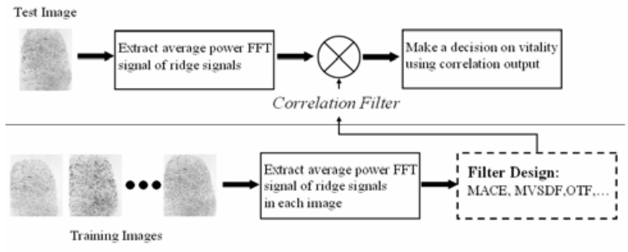

Fig. 6 Fake fingerprint detection using a correlation filter

The technique consists of two stages, namely the enrollment and the verification [15]. During the enrollment stage, multiple training images from each individual are captured and the ridge signals are extracted to construct a correlation filter. In verification stage, the ridge signal from the test image is extracted and then convolved with the individual correlation filter of each individual. The result is analyzed.

To measure the individual pore spacing, the following training process is applied;

1) Capture fingerprint training images of each individual (live) and extract the average power spectrums of ridges from these images [5].
2) Construct an optimal tradeoff correlation filter for each individual with the following equation [16].

$$h_{OTF} = (D+\alpha I_d)^{-1} G (G^{+} (D+\alpha I_d)^{-1} G)^{-1} c \qquad (1)$$

where G is a matrix composed of each training sample $G=[g_{1,} g_{2,...} g_N]$, and g_i represents $k \times 1$ column vector. D is a $k \times k$ diagonal matrix which entries along the diagonal are obtained by averaging $|g_i(k)|^2$, i=1,2,...,N. And I_d is a $k \times k$ covariance matrix of the white noise. c is the column vector which represents correlation peaks.

In our algorithm, the correlation peak values are all 1. α is a parameter indicating the relative importance of noise tolerance and peak sharpness in the filter design. We fix α value as 0.0001 empirically. To measure the correlation output of a test image, the following test process is applied;

3) Capture a fingerprint image of each individual (live and fake) and repeat step 1 and finally obtain the average power spectrum as the input signal.
4) Calculate the correlation output and the decision is made based on the vitality according to the results. The test equation is followed by:

$$X^T h = c' \quad (2)$$

where X is a $k \times 1$ matrix of input signal and c' is the correlation output value.

We expect that, when a live finger of each individual comes to the sensor, the correlation output is close to value 1. However when a fake finger is presented, pores do not exist, hence the correlation output is far from 1. We compute the Euclidean distance between the correlation output and the value 1 as the first static measure. And these calculated values are normalized in the range [-1, 1].

$$Feature\_1 = \sqrt{(1-c')^2} \quad (3)$$

B. Analysis of Noise Residue and Statistical Properties

We calculate the residual noise and statistical properties by using the method suggested in [7, 8]. Let X and X' are original and de-noised images. We de-noise the image by using several conventional filters such as Gaussian, median, Wiener and also *Dmey wavelet*. The filter sizes of first three are set to be equal. We calculate the standard deviation of noise residual image and normalize these values in the range [-1, 1] as shown in equation (4, 5).

$$\sigma = Std(X - X') \quad (4)$$

$$Feature\_2 = normalize(\sigma) \quad (5)$$

And seven first order statistics of image are also calculated and used as 3rd ~9th feature. These features are also normalized.

IV. Experimental Results

A. Data Set

A set of fingerprint images was acquired through the optical fingerprint sensor manufactured by NITGEN, Inc. The size of the image is 248×292 pixels with 500dpi resolutions. And fingerprint images were collected from both live and fake fingers. In order to perform aliveness detection using correlation filters, there are two ways to collect the data set. First, to construct a correlation filters for each person, we collected 10 fingerprint images from 110 cooperative subjects using the dab method. When collecting training images, we ask users to dry their fingers. Second, to analyze the individual pore spacing, the coarseness and the gray-value distribution of images, a set of fingerprint images from 110 subjects is collected. To generate the fake fingerprint images, the with-cooperation method is used [3]. Finger molds were created by using dental impression materials because of their detailed description of finger. And gummy fingers were used in making fake fingers. Examples of the live and fake images are shown in Fig. 7.

Fig. 7 Examples of live (top) and fake (bottom) images

B. Results

First, we analyze each feature (pore spacing, noise and the first order statistics) by the best classification rate. In order to find the best classification rate of each feature, we adjust simply the threshold of the similarity score which is the boundary between the live and fake fingers. Classification rate is defined as the percentage of live and fake fingerprints that are correctly classified. Table I shows the performance comparison between the 'static measure' in [5] and the proposed correlation filter method. The correlation filter method considering the individuality of pore spacing and thus it outperforms the static measure [5], which based on the simple thresholding technique.

TABLE I
COMPARISON BETWEEN *STATIC MEASURE* [5] AND PROPOSED CORRELATION FILTER METHOD

Methods	Classification rate (%)
Static measure [5]	70.11
Correlation filter (using 3 training images)	76.74
Correlation filter (using 5 training images)	77.79
Correlation filter (using 7 training images)	78.96
Correlation filter (using 9 training images)	**80.69**

Table II shows the classification rates of using noise features. We tested *Dmey wavelet*, Gaussian, median and Wiener filter. The classification rate of median filter has the best performance. However the performance of Wiener filter is the worse compare to others because the high frequency spectrum of a dry fingerprint image is different from white Gaussian noise.

TABLE II
CLASSIFICATION RATES OF DE-NOISING FILTERS

De-noising filters	Classification rate (%)
Dmey wavelet de-noising [7]	73.15
Gaussian filter de-noising	73.61
Median filter de-noising	**75.46**
Wiener filter de-noising	59.72

The performances of the first order statistics of image are shown in Table III. Most of these features are weak to apply directly. However, skewness has the best performance in these features because it reflects the gray-value distribution of dry fingerprint image.

TABLE III
CLASSIFICATION RATES OF 7 FIRST ORDER STATISTICS

First order statistics	Classification rate (%)
Energy	54.17
Entropy	51.39
Median	58.80
Variance	54.17
Skewness	**61.57**
Kurtosis	59.72
Coefficient of variation	55.09

The best features in each feature set (correlation filter with 9 training images, median filter de-noising, skewness) were selected and fused in score level. The distribution of these features is shown in Fig. 8. For the score level fusion we applied nine classifiers [17-18]. The parameters of each classifier are shown in Table V. The best classification rates of 9 classifiers were compared in Table IV. The optimal parameters of each classifier were experimentally determined.

TABLE IV
BEST CLASSIFICATION RATES OF 9 CLASSIFIERS

Classifier	Classification rate (%)
RM(Reduced Multivariate polynomial)	**85.19**
PNN(Probabilistic Neural Networ)	71.76
BP(Back Propagation)	70.05
SBP(Stochastic Back Propagation)	81.02
RBP(Recurrent Back Propagation)	80.56
RBF (Radial Basis Function Classifier)	58.80
SVM_RBF(Support Vector Machine with RBF kernel)	69.50
SVM_Poly(Support Vector Machine with Polynomial kernel)	81.48
NN(Nearest Neighbor)	70.83

TABLE V
PARAMETER ADJUSTMENT OF 9 CLASSIFIERS

Classifier	Ranges of Parameters		
RM	Polynomial Order (1~10)		
PNN	Parzan window width (0.05 ~ 0.15 interval 0.01)		
BP SBP RBP	Hidden units	Convergence Criterion	Convergence Rate
	3~7	0.001~0.011 interval 0.002	0.1
RBF	Hidden units (3~23)		
SVM_RBF	Window width	Solver	Slack
	0.41~0.01 Interval 0.1	Perceptrom	0.1
SVM_Poly	Polynomial Order	Solver	Slack
	1~6	Perceptrom	0.1
NN	Number of Neighbor (1~10)		

The summary of the best classification rate is presented in Table VI. The final performance of our method goes up to approximately 85%.

TABLE VI
CLASSIFICATION RATES OF EACH METHOD

Methods	Classification rate (%)
Feature 1 (correlation filter using 9 image)	80.69
Feature 2 (median de-noising)	75.46
Feature 3 (skewness)	61.57
RM	**85.19**

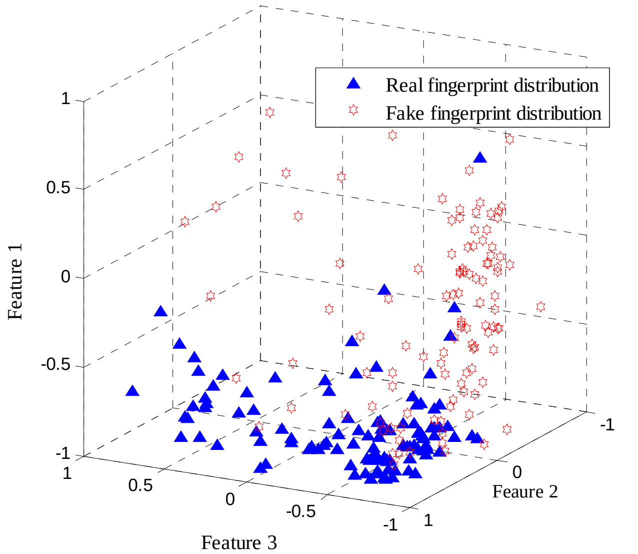

Fig. 8 Distribution of selected features

V. CONCLUSION

This paper describes a new method for detecting fake fingers by using multiple static features. Static features which are detectable in an image have advantages such as convenience and good performance. Individual pore spacing, noise and first order statistics of image are used as our static features. We also propose Correlation filter for consider individual pore spacing. Both aliveness score of each feature and classification rate are analyzed and we obtain very promising results. Experimental results show that the proposed method has approximately 85% classification rate only by using a single image.

ACKNOWLEDGMENT

This work was supported by the Korea Science and Engineering Foundation (KOSEF) through Biometrics Engineering Research Center at Yonsei University.

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