FINGERPRINT LIVENESS DETECTION USING LOCAL RIDGE FREQUENCIES AND MULTIRESOLUTION TEXTURE ANALYSIS TECHNIQUES

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ABSTRACT

It has been demonstrated that simple and inexpensive techniques are sufficient to spoof fingerprint scanners. Previously, effective use of physiological phenomenon of perspiration is shown as a countermeasure against such attacks. These techniques require more than one image for performing the liveness check and hence may not be suited for on-line processing. In this work, a liveness measure based on single image is developed. The inherent texture and density differences between 'live' and 'not live' fingerprint images are exploited. Multiresolution texture analysis techniques are used to minimize the energy associated with phase and orientation maps. Cross ridge frequency analysis of fingerprint images is performed by means of statistical measures and weighted mean phase is calculated. These different features along with ridge reliability or ridge center frequency are given as inputs to a fuzzy c-means classifier. The proposed algorithm was applied to a dataset of approximately 58 live, 50 spoof and 28 cadaver fingerprint images, from three different types of scanners. An error rate of 1.4% is achieved. The algorithm provides a faster technique for doing a liveness test which relies on only one fingerprint image.

Keywords: fingerprints, liveness, ridge frequency analysis, multiresolution texture analysis, first and second order statistical features, fuzzy c-means classifier.

1. INTRODUCTION

With the development of tightly connected, networked societies, personal identification has become critically important. Biometric identifiers are replacing traditional identifiers, as it is difficult to steal, replace, forget or transfer them. Fingerprint recognition systems (FRS) are oldest and most popular biometric. Automatic fingerprint matching involves determining the degree of similarity between two fingerprint impressions by comparing their ridge structures and/or the spatial distributions of their minutiae points. Previous work shows that it is possible to spoof different fingerprint technologies by means of relatively crude and inexpensive methods. Liveness detection is defined as a method to assist the fingerprint scanner in determining whether the introduced biometric is coming from a live source. Liveness tests have been demonstrated as a method to elude attacks that use charade fingers.

Different spoofing techniques have been reported, using fake fingers made of gelatin (gummy fingers), moldable plastic, clay, play-doh, wax, and silicon, developed from casts of live fingers or latent fingerprints [1, 2, 3, 4, 5, 6]. Spoofing is defined as fraudulent entry of an unauthorized personnel into a fingerprint recognition system by using a faux fingerprint sample [1]. Our laboratory has also demonstrated vulnerability to spoofing using dental material for preparing casts and Play-Doh for creating molds [5]. Verification rate varied from $45\% - 90\%$. Furthermore at our laboratory different scanner technologies including optical, capacitive AC, capacitive DC and opto-electrical were tested using cadaver fingers and a verification rate of 90% was achieved [5].

It has been shown that a perspiration pattern can be used as a measure of "liveness" detection in case of fingerprint matching systems [5, 7]. This pattern evolves in time due to the physiological phenomenon of perspiration [8]. Previous algorithms developed at our lab are based on various signal and image processing based techniques along with different classifiers and are reported to produce classification results from 45% to 100%. The major drawback associated with these techniques is the mandatory requirement of availability of at least two time-series captured images of that finger. Hence these techniques are limited in their applications, especially where on-line processing is required. In this work, a new technique that requires only one image per class to do further analysis is proposed. Multiresolution texture analysis along with inter-ridge frequency analysis of fingerprint images is performed to distinguish 'live' fingers. This method relies on the subtle characteristics of the underlying fingerprint texture, which are different for different types of images as shown in figure (1).

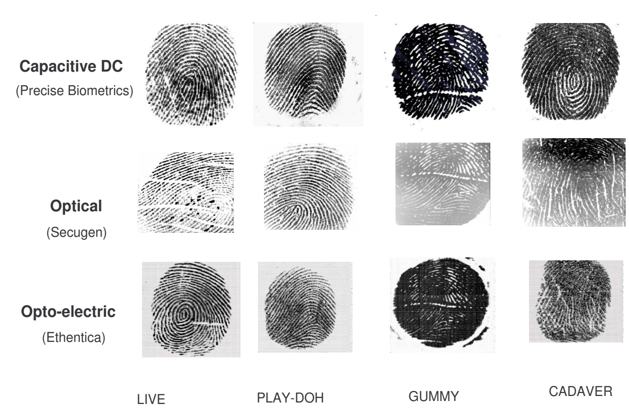

Fig. 1. Fingerprint image samples for live, play-doh spoof, gummy and cadaver are shown in columns, for three different fingerprint sensing technologies, namely capacitive DC, optical and opto-electrical, shown in rows.

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2. LIVENESS DETECTION ALGORITHM

The complete algorithm can be divided into three parts. The first part includes multiresolution texture analysis of the fingerprint images. The second part is the inter-ridge frequency analysis of the fingerprint images and design of features. Fuzzy c-means classifier analysis based on the different features formulated in first two parts forms the third part.

2.1. Multiresolution texture analysis techniques

Earlier work in our lab [5, 7, 8] has shown that the gray level associated with the fingerprint pixels can be used to analyze liveness associated with that fingerprint image. Also, visually it is very pertinent that gray level distribution in a fingerprint image changes when the physical structure changes. Several texture features are used to quantify this information. Texture features can be divided into first, second and higher order statistics [9]. The gray level distribution of the single pixels is modelled as first order statistics while second order statistics refer to the joint gray level function between pair of pixels.

2.1.1. First order features

These features directly refer to the visually observed difference in the 'live' and 'not live' fingerprints. This was confirmed by changes in the types of histograms of different fingerprints. If $H(n)$ indicates the normalized histogram, the first order features used for the this work are as follows,

- Energy:

$$e = \sum_{n=0}^{N-1} H(n)^2 \tag{1}$$

- Entropy:

$$s = -\sum_{n=0}^{N-1} H(n) \log H(n) \tag{2}$$

- Median:

$$M = \arg\min_a \Big(\sum_n H(n)|n-a|\Big) \tag{3}$$

- Variance:

$$\sigma^2 = \sum_{n=0}^{N} (n-\mu)^2 H(n) \tag{4}$$

- Skewness:

$$\gamma_1 = \frac{1}{\sigma^3} \sum_{n=0}^{N-1} (n-\mu)^3 H(n) \tag{5}$$

- Kurtosis:

$$\gamma_2 = \frac{1}{\sigma^4} \sum_{n=0}^{N-1} (n-\mu)^4 H(n) \tag{6}$$

- Coefficient of variation:

$$cv = \frac{\sigma}{\mu} \tag{7}$$

where, N is equal to number of bins and μ and σ are the mean and the standard deviation, respectively.

2.1.2. Second order features

In order to represent second order statistics, co-occurrence matrix (Υ) was calculated, which essentially is the joint probability function of the two image elements in a given direction and distance, say, $\Upsilon(n, m|d, \theta)$. As suggested by Jain et. al. [10, 11], symmetric directions $\theta = 0^o, 45^o, 90^o, 135^o$ were used to avoid dependency on the direction. Based on the definition of the co-occurrence matrix, following two secondary features were used,

- Cluster Shade (CS):

$$CS = \frac{\sum_{n=0}^{N} \sum_{m=0}^{N} (n-\mu_x+m-\mu_y)^3 \Upsilon(n,m)}{(\sigma_x^2+\sigma_y^2+2\rho\sigma_x\sigma_y)^{3/2}} \tag{8}$$

- Cluster Prominence (CP):

$$CP = \frac{\sum_{n=0}^{N} \sum_{m=0}^{N} (n-\mu_x+m-\mu_y)^4 \Upsilon(n,m)}{(\sigma_x^2+\sigma_y^2+2\rho\sigma_x\sigma_y)^{2}} \tag{9}$$

Multiresolution second order texture analysis was performed using bi-orthogonal wavelets. Bi-orthogonal pyramid of the fingerprint image was computed and then a fixed distance Υ was calculated at each level of the pyramid.

2.2. Fingerprint local-ridge frequency analysis

In a fingerprint image, that part of the image, which does not have minutiae points in a near vicinity, can be represented by modelling the pixels along the ridges as a sinusoidal-shaped wave. The direction of the local ridge orientation is orthogonal to this direction [11], thus making local-ridge frequency an important property of an image.

While performing the analysis on the block of size $w \times w$, and for each block centered at (i, j), the local frequency was calculated as [11],

$$\Gamma(i,j) = \frac{\sum_{u=-w_\gamma/2}^{w_\gamma/2} \sum_{v=-w_\gamma/2}^{w_\gamma/2} \Psi_g(u,v)\mu(\Gamma(i-uw, j-vw))}{\sum_{u=-w_\gamma/2}^{w_\gamma/2} \sum_{v=-w_\gamma/2}^{w_\gamma/2} \Psi_g(u,v)\delta(\Gamma(i-uw, j-vw))} \tag{10}$$

where,

$$\mu(x) = \begin{cases} 0 & if\ x \leq 0 \\ x & otherwise \end{cases}$$

$$\delta(x) = \begin{cases} 0 & if\ x \leq 0 \\ 1 & otherwise \end{cases}$$

Ψ_g is a bi-orthogonal kernel and w_γ is the kernel size.

Due to the scalable nature of the wavelets, $\Gamma(i, j)$ is also scalable. For the part of the fingerprint image, where inter-ridge distance hardly changes results in high energy in the LL bands and can be ignored during synthesis phase.

Statistical analysis of local ridge frequencies gives us following features,

- ridge mean (μ_r)
- ridge median (M_r)
- ridge variance (γ_r)
- ridge standard deviation (σ_r)

The fingerprint image may contain many artifacts and hence orientation fields generated from the fingerprint images can not be directly used. Ridge reliability was calculated using alignment of the ridge with the other adjacent ridges and the length of the connected ridge segments.

2.3. Fuzzy c-means classifier

Fuzzy c-means clustering (FCM) is very different from hard k-means, in the sense that, it does not employ hard threshold, instead employs fuzzy partitioning such that a data point can belong to all groups with different membership grades between 0 and 1. This is important feature for liveness detection to improve the sensitivity. An iterative approach to find cluster centers (centroids) that minimize a dissimilarity function is adopted.

The membership matrix (U) is randomly initialized using,

$$\sum_{i=1}^{c} u_{i,j} = 1, \forall j = 1, ..., n \tag{11}$$

The dissimilarity function is given as,

$$J(U, c_1, c_2, ..., c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m d_{ij}^2 \tag{12}$$

where, u_{ij} is between 0 and 1,
c_i is the centroid of cluster i,
d_{ij} is the Euclidean distance between i^{th} centroid (c_i) and j^{th} data point,
$m \in [1, \infty]$ is a weighting exponent.

To reach the minimum dissimilarity function following two conditions are used,

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m} \tag{13}$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}} \tag{14}$$

The centroids c_i are calculated using equation (13). By iteratively updating the cluster centers and the membership grades for each data point, FCM iteratively moves the cluster centers within data set. Dissimilarity between two clusters is calculated using equation (12). The iterative process is stopped when the improvement over previous iteration is below the threshold.

Different features were derived from local ridge frequencies in fingerprint images and from the multiresolution texture analysis of fingerprint images, as explained in previous two subsections. PCA is performed on the feature set. These features are given as inputs to the FCM classifier. The overview of the algorithm is shown in figure (2).

2.4. Data management

Data previously collected in our lab is used to test the algorithm. This data set is diverse as far as age, sex, and ethnicity is concerned. This data set is comprised of different age groups ,ethnicities, and approximately equal numbers of men and women. The data was collected using three different fingerprint scanners, with different underlying technologies, Secugen (model FDU01), Ethentica (model Ethenticator USB 2500)and Precise Biometrics (model PS100) with optical, electro-optical and capacitive DC technique of capturing fingerprint, respectively. For spoof category, a cast was made from each live subject using dental material and spoofs were created from Play-Doh using the procedure given in [5]. Images from cadaver subjects were collected in collaboration with MUSCULOSKELETAL Research Center at West Virginia University (WVU). Protocols for data collection from the subjects were followed that were approved by the West Virginia University Institutional Review Board (IRB) (HS#14517 and HS#15322). The data set consists of 130 to 136 fingerprints from live, spoof, and cadavers, depending on the scanner used. Table (1) summarizes the available data. Differences in the number of images per scanner are due to inclusion criteria which requires an accepted enrollment image within five tries. Image collection was performed using custom software developed from device SDKs. All algorithm development was performed using MATLAB.

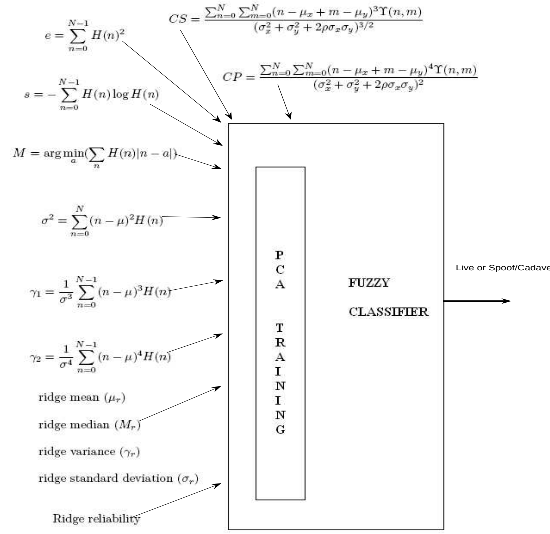

Fig. 2. Algorithm overview.

Table 1. Data set: Distribution

	Capacitive DC Precise Biometric	Electro-optical Ethentica	Optical Secugen
Live	58	55	58
Spoof	50	50	52
Cadaver	33	22	28

3. RESULTS

This section shows the results generated after applying the algorithm. The training was performed separately for all the three scanners. 35 live and spoof images were used for training. Cadaver images used for training were 15, 12 and 15 for Precise Biometrics, Ethentica and Secugen, respectively. The results are as shown in figure (3). The results are plotted using non-linear sammon mapping. The two axes are the first two principle components. The left centroid is for ‘live’ data while the right side centroid is for ‘not live’ data. Classification rates of 97.3%, 96.5% and 92.3% were achieved using the proposed algorithm for Secugen, Precise Bioemtrics and Ethentica respectively.

4. DISCUSSION AND FUTURE WORK

The research presented here presents a new FCM based method which is based on utilizing the density and structure of fingerprint images measured directly from scanner. Thus this method, being purely software based, is cheaper and more flexible for future adaptations. This method captures and characterizes the local ridge frequencies, thus separating live fingers from spoof or dismembered fingers.

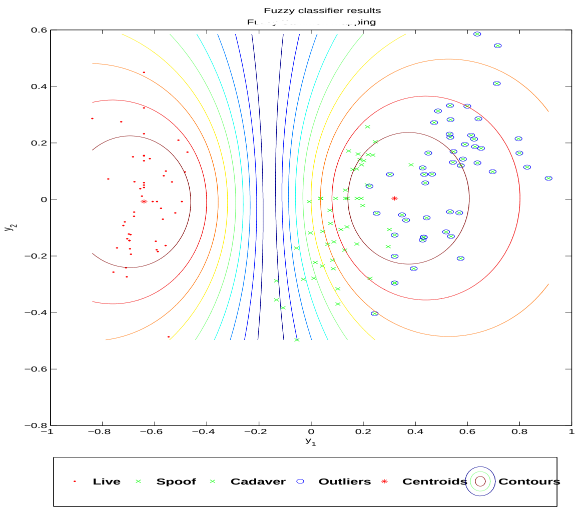

Fig. 3. Result of the FCM classifier. The left centroid is for live fingerprints and right centroid is for not live data.

Liveness detection has been suggested as a countermeasure against spoofing of fingerprint scanners. Previously, to strengthen fingerprint recognition, several liveness measures including pulse, pulse oximetry, electrocardiogram and temperature detection are suggested. All these liveness detection methods are hardware based and hence are expensive.

The presented method is not based on the algorithm given in [5] and its enhanced version [7], where perspiration phenomenon is used for liveness testing. While these algorithms were able to attend approximately $90\% - 100\%$ classification, the presented algorithm was able to overcome the dependence on more than one fingerprint image.

The algorithm does not depend on the physiological phenomenon of perspiration and might work better than previous algorithms under various environmental conditions. If a live person were to introduce artificial deformation, then he/she might get falsely rejected, as the algorithm relies on the underlying texture and density of the fingerprint. But, no authorized personnel would want to get rejected and hence there is no motive to introduce artificial deformations by an authorized person.

While the algorithm is shown to give 95.36% classification for the limited data used, more data with multiple scanners and with different underlying technologies is required to validate the perspiration phenomenon across the population and also validate the capabilities of the presented work. It is desired to test the performance of the algorithm to work under different environmental settings including hot weather, cold weather and different finger conditions including dirty fingers, wet fingers and dry fingers. The algorithm can be evaluated in the light of the fact that the above conditions are problematic for performing the fingerprint recognition, irrespective of liveness detection. The algorithm is developed using MATLAB 6.5, using pentium processor, with 1GB RAM. The entire algorithm steps take roughly 2 seconds to formulate results.

5. CONCLUSION

A new approach to detect "liveness" associated with fingerprint scanners is proposed. The approach is based on underlying texture and density of the fingerprint images. The algorithm combines the features derived from multiresolution texture analysis as well as derived from local ridge frequency analysis. The features are further processed using FCM and error rates are calculated. Based on the association of all the points to particular type of a class, the classification rates are calculated. The training is performed through PCA and first two components are used to map the data non-linearly. This method is tested for three different types of scanner technologies, namely optical, opto-electrical, capacitive DC. Overall 95.36% classification rate is obtained. Advantages of this method are that it is purely software based and only requires one image.

6. REFERENCES

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