Texture and Wavelet-Based Spoof Fingerprint Detection for Fingerprint Biometric Systems

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Abstract

This paper describes an image-based system to detect spoof fingerprint attacks in fingerprint biometric systems. It is based on the observation that, real and spoof fingerprints exhibit different textural characteristics. These are based on structural, orientation, roughness, smoothness and regularity differences of diverse regions in a fingerprint image. Local binary pattern (LBP) histograms are used to capture these textural details. Wavelet energy features characterizing ridge frequency and orientation information are also used for improving the efficiency of the proposed method. Dimensionality of the integrated feature set is reduced by running Pudil’s Sequential Forward Floating Selection (SFFS) algorithm. We propose to use a hybrid classifier, formed by fusing three classifiers: neural network, support vector machine and k-nearest neighbor using the “Product Rule”. Classification rates achieved with these classifiers, including a hybrid classifier are in the range ~94% to ~97% Experimental results indicate that, the new liveness detection approach is a very promising technique, as it needs only one fingerprint and no extra hardware to detect vitality.

Keywords-Fingerprints, Local binary pattern, Liveness, Texture features, Wavelets.

1. Introduction

Biometric systems are being increasingly deployed in a wide range of authentication applications such as: civil identification, travel documents, airport and border entry control, network security, point-of-sale authentication, electronic banking, finance and medical applications, and most importantly countering terrorist threats. Popularity of these systems is attributed to the fact that, biometric features offer usability advantages over conventional password or token-based identification schemes.

Of all these biometric systems, fingerprint recognition systems are the most popular and are extensively being used. However, recently it is demonstrated that, these systems are vulnerable to various kinds of threats like: spoof finger attack at the sensor, attack on software modules (e.g. Trojan horse attack on feature extractor or the matcher), replay attacks, modifying enrolled templates, attacking channel between template databases and matching module, etc [1].

This paper proposes a new texture and wavelet-based liveness detection method utilizing integrated gray level texture, ridge frequency and orientation information to alleviate the problem of spoof fingerprint attacks at the sensor level.

Local binary pattern (LBP) histograms are used to extract spatial gray level details. Ridge frequency and orientation details are exploited by decomposing a fingerprint in various approximation and detail subbands using different wavelet filters like Daubechies order 4, Biorthogonal 1.3 and Morlet. Feature vectors are formed by fusing local binary pattern histograms and wavelet energy features. Then Sequential Forward Floating Selection (SFFS) search is applied to obtain a feature set of reduced dimension. We propose to use a hybrid classifier formed by fusing neural network, support vector machine and k-nearest neighbor using the “Product Rule”.

Schematic diagram of a proposed liveness detection method is shown in Fig. 1.
Spoof fingerprint database contains Fun-Doh (Play-Doh) and Gummy fingerprints created using different combinations of materials for casts and moulds. Overall classification rates achieved with all the classifiers, including a hybrid classifier are in the range ~94% to ~97%.

Thus, incorporating proposed liveness detection technique in the optical fingerprint scanner can safeguard a fingerprint biometric system from spoof fingers made of dough (clay) or synthetic gum.

The following sections give details of the proposed method. Related works and advantages of the proposed work over some existing works are discussed in Section 2. Proposed method is described in Section 3. This section describes LBP histogram-based texture analysis and wavelet energy feature extraction. Real, Fun-Doh spoof and Gummy spoof fingerprint databases are also described here. Experimental results are presented in Section 4. Finally, Section 5 concludes the paper and gives some future directions.

2. Related works

Putte and Keuning [2], Matsumoto et al. [3] and many other researchers demonstrated simple ways of spoofing fingerprint biometric systems using artificial fingers made of clay, gelatin, or silicone. Liveness detection based on static and dynamic properties of a finger is a solution to prevent spoof fingerprint attacks. Static properties are: temperature, odor, impedance and electrical conductivity of the skin, laser detection of 3-D finger surface and pulse, and spectroscopy, whereas dynamic properties are: skin-perspiration, pulse oximetry, blood pulsation, E.C.G., and skin elasticity [4].

Use of fingerprint scanners for observing perspiration behavior of human fingers is proposed in [5]-[6]. These methods need finger to be placed on a scanner surface for 2 seconds (or 5 seconds) so that perspiration information is available. Therefore, these methods are slow, and can not be used for real-time authentication applications having millions of identities enrolled.

Another skin-perspiration-based method using a single image is proposed in [7]. Method [7] obtains static perspiration information from a single image and quantifies it using wavelet signal processing. Researchers [7] have not considered dynamic nature of perspiration phenomenon.

However, perspiration basically is a time-dependent dynamic process. Perspiration information keeps on changing with respect to time (i.e. more time gives more perspiration information, and therefore results in a more accurate system). Thus, single-image-method utilizing perspiration information results in a low accuracy of the system.

To alleviate these problems, we propose a new texture-based method that uses only the first fingerprint image. Since proposed method detects vitality using only one image, it can be effectively used to detect spoof fingerprints, encountered especially in unattended real-time authentication applications. Furthermore, it will reduce the cost of a fingerprint biometric system, as no additional hardware is required.
3. Proposed approach

3.1. Real, Fun-Doh and Gummy fingerprint databases

Fingerprint images are acquired from 185 real, 90 Fun-Doh and 150 Gummy fingers using Secugen optical fingerprint scanner (Model- HFDU01). Casts and moulds of spoof fingers are made by using different combinations of materials.

Materials used for cast are: M-seal adhesive (i.e. plumber’s putty), dental impression materials (i.e. Aquasil soft putty-regular set silicone, PYRAX-RR cold cure, Zelgan 2002 powder), Fun-Doh (i.e. playing clay), soft plastic, Fevi-gum (i.e. gelatin), and general purpose silicone sealant. Fun-Doh and Fevi-gum are also used to create moulds. Fig. 2 shows parts of real, Fun-Doh, and Gummy fingerprint images.

3.2. Texture feature extraction

In this work, a new texture-based liveness detection method based on local binary patterns, and wavelet transform is proposed to safeguard fingerprint biometric systems from spoof fingerprint attacks. It is observed that, because of different characteristics of surfaces of real and spoof fingers, ridge lines of real, Fun-Doh and Gummy spoof fingerprints exhibit different gray level characteristics. For example, surface texture of a real finger depends on various factors like: elasticity of skin, presence of pores, natural perspiration phenomenon, age of person, and presence of sweat on the surface, etc. Therefore, ridge pixels of a real fingerprint exhibit wide and random variation of gray level characteristics, unlike, Fun-Doh and Gummy finger surfaces which are made of artificial materials like dough (clay) and Fevi-gum (gelatin), respectively. Material characteristics of dough and Fevi-gum do not change with ridge pixels. Due to this, ridge lines of spoof fingers show uniform gray level characteristics along ridges. Further, physical properties of these materials are different from those of human skin. Real and spoof fingers have significant differences in inter-ridge distances and ridge frequencies also. Moreover, ridge widths are also observed to be different for real and spoof fingers. Therefore, spoof fingers exhibit different gray level characteristics than those of real fingers. This fact is used here to differentiate a real finger from a spoof one.

3.2.1. LBP histogram features

Ojala et al. [8] have proposed a theoretically and computationally simple approach for classifying wide variety of texture images. We can define a texture $T$ in a local neighborhood of a pixel $c$ in a fingerprint image as [8]:

$$T = t(g_c, g_0, \ldots, g_{p-1})$$

(1)

This texture definition provides the joint distribution of the gray levels of $p(p > 1)$ image pixels, where the gray value $g_c$ corresponds to the gray value of the center pixel $c$ of the local neighborhood, and $g_p (p = 0, \ldots, p - 1)$ correspond to the gray values of $p$ equally spaced pixels on a circle of radius $R > 0$, that form a circularly symmetric neighbor set.

We subtract the gray value of the center pixel $g_c$ from the gray values of the circularly symmetric neighborhood $g_p (p = 0, \ldots, p - 1)$ giving [8]:

$$T = t(g_c, g_0 - g_c, g_1 - g_c, \ldots, g_{p-1} - g_c)$$

(2)
Then, we define a function $s(x)$ as:

$$s(x) = 1, \text{ if } x \geq 0, \text{ else } s(x) = 0.$$  \hspace{1cm} (3)

The local binary pattern [8] is calculated by:

$$\sum_{p=0,\ldots,p-1} s(g_p - g_x)2^p$$  \hspace{1cm} (4)

We calculate rotation invariant uniform local binary pattern histograms of 10 bins, 18 bins and 26 bins. The features extracted from these histograms are concatenated to give a 54-dimensional feature vector. An example of a feature extraction by LBP histogram method is shown in Fig. 3.

3.2.2. Wavelet energy features

Recently, multiresolution approaches based on wavelet transform and wavelet frames have been used for texture characterization [9]. Wavelets provide frequency and orientation information of textures, which is useful for texture classification.

In wavelet decomposition, an image is decomposed in four subbands leading to: the approximation subband containing global low frequency information, and three detail subbands containing high frequency information.

In the proposed method, an image is decomposed in $J = 4$ levels to give $3 \times J + 1 = 13$ subbands. Daubechies order 4, Biorthogonal 1.3 and Morlet wavelet filters are used for image decomposition. The approximation image is not considered, since it does not contain high frequency information. For each decomposition, the energies are measured by calculating the mean and standard deviation of each detail subband.

The wavelet energy features calculated for each subband are concatenated to LBP histograms obtained earlier in section 3.2.1. Then, Pudil et al.’s [10] Sequential Forward Floating Selection (SFFS) feature selection method is used to decorrelate features and to obtain a feature vector of reduced dimension.

3.2.3. Sequential Forward Feature Selection (SFFS)

In Pudil et al.’s [10] SFFS, initially we assume that $k$ features have already been selected from the complete set of measurements, $Y = \{y_j | j = 1,\ldots, D\}$ to form an optimal set, $X_k$. Algorithm consists of two main steps: Inclusion and Conditional exclusion. Inclusion is a forward optimization step that selects best feature, $x_{k+1}$ from the set of available measurements, $Y - X_k$ to form a feature set $X_{k+1}$. The second step, conditional exclusion deletes the least significant feature from the set $X_{k+1}$. The SFFS method dynamically changes number of features included or deleted at each step, hence called floating search method. We use “1-Nearest Neighbor error” as a criterion function.

After running SFFS, we create a library of integrated feature vectors; consisting of both LBP histogram features and wavelet energy features. We use 185 real, 90 Fun-Doh and 150 Gummy fingerprint images to create a feature library.

4. Experimental results

4.1. Classification results

We test integrated feature set using three classifiers. The first, back-propagation neural network is selected, as pattern classification is one of the important fields of application of neural networks. Support vector machine is chosen as a second classifier, as it is a state-of-the-art linear classifier. SVM maps input vectors to a higher dimensional space where a maximal separating hyperplane is constructed. Radial basis function (RBF) kernel is used with its parameters ‘C’ and ‘gamma’ as 1 and 2.3, respectively. Third, k-nearest neighbor is also used, as it a well-known decision rule widely used in pattern
Table 1: Confusion matrices for real, Fun-Doh and Gummy fingerprint classification, Classifiers used: (1) Neural network, (2) Support vector machine, (3) K-nearest neighbor, and (4) Hybrid classifier; No. of fingerprints of each class: Real-185, Fun-Doh-90, and Gummy-150.

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<thead>
<tr>
<th></th>
<th>Neural Network</th>
<th>K-Nearest Neighbor</th>
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<td></td>
<td>Assigned Class</td>
<td>Overall</td>
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<td></td>
<td>Class. Rate (%)</td>
<td>Class. Rate (%)</td>
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<tr>
<td>True class</td>
<td>Assigned Class</td>
<td>Overall Class. rate (%)</td>
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<td>Real</td>
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<tr>
<td>Fun-Doh</td>
<td>07 83</td>
<td>92.22</td>
</tr>
<tr>
<td>Gummy</td>
<td>09 141</td>
<td>94.00</td>
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Support Vector Machine: Overall Classification Rate = 94.59

Hybrid Classifier: Overall Classification Rate = 97.41

Fig. 4. Overall classification rates achieved for real, Fun-Doh and Gummy fingerprint classification by varying: (a) No. of folds for cross-validation (N), (b) value of percentage data split (%), Classifier used: Hybrid classifier, No. of fingerprints of each class: Real-185, Fun-Doh-90, and Gummy-150.

Fig 5. Comparison with Bozhao and Schuckers [7] method for real and spoof fingerprint classification.
classification. Finally, all the three classifiers are fused using the “Product Rule” to build a hybrid classifier [11].

Results obtained with all the classifiers are reported in Table 1. It is observed that, results with a hybrid classifier are better than the other three independent classifiers. We also performed cross-validation testing for real, Fun-Doh and Gummy fingerprint classification by varying the number of folds (N). Overall classification rates achieved with a hybrid classifier are presented in Fig. 4.

Furthermore, performance of a hybrid classifier is checked by varying the value of “percentage data split” for training. In this testing option a database is split in two parts. Certain percentage of a database is used for training and rest is held out for testing. Overall classification rates achieved for real, Fun-Doh and Gummy fingerprint classification are reported in Fig. 4.

The experiments are performed on Pentium-4, 2.8 GHz Processor with 2 GB RAM, running Windows XP. Time required for LBP feature extraction is ~0.672 seconds, whereas time for wavelet feature extraction using 4 levels of decomposition is only ~0.0157 seconds.

4.2. Comparison with related work

Bozhao and Schuckers [7] have proposed a fingerprint liveness detection method using a single image only; therefore we select their work for comparison. We used the optical fingerprint scanner for database creation, so results are compared for Secugen optical fingerprint scanner case (see Fig. 5). We compare results achieved with a proposed hybrid classifier with results in [7]. It is observed that, proposed method clearly outperforms approach in [7] for both real and spoof cases. Researchers [7] have obtained perspiration information from a single image and quantified it using wavelet signal processing. However, as seen from the results, texture details used in the proposed method provide more accurate results, than the results in [7].

5. Conclusions and future directions

In this paper, a new single-image-based method utilizing integrated gray level texture and wavelet energy information for spoof finger detection is presented.

It is observed that, textural characteristics of real fingerprints are different from those of spoof fingerprints. These textural characteristics are analyzed using LBP histogram method and wavelet-based multiresolution analysis techniques. Classification rates achieved with various classifiers, including a hybrid classifier are in the range ~94% to ~97%. Experimental results indicate that, the proposed method is very efficient than the other methods proposed in the literature, as only one image is sufficient to defend spoof attacks. Also it will reduce the cost of a fingerprint biometric system, as no additional hardware is required.

Following improvements in the proposed method are possible:

1. In wavelet analysis, performance of the method relies more on underlying wavelet used. More texture information can be extracted by the proper selection of wavelet to maximize the correlation in signal decomposition. One can explore further real and spoof fingerprints of various kinds and study their textural characteristics. This will help to design a new wavelet which will process textural characteristics of fingerprints in a better way.

2. Also, one can work on automatic selection of optimal wavelet and wavelet decomposition level.

6. References


