Integrating Liveness Detection Technique into Fingerprint Recognition System: A Review of Various Methodologies Based on Texture Features

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Abstract Automatic fingerprint recognition systems can be deceived by spoof attack wherein an artificial fingerprint from synthetic finger fabricated using material like silicone, latex, is presented for verification. This is a serious issue as an adversary can impersonate a legitimate user of the system, especially when fingerprint technology is used as a security measure instead of conventional passwords. The solution is to integrate a liveness detection technique into the fingerprint recognition system to ensure the presence of a legitimate user. One approach is to use a dedicated hardware module with liveness detection capability, but it is intrusive, non-flexible, costly and needs user co-operation. Another approach is to use a dedicated software module with liveness detection capability, which is non-intrusive and user-friendly. Among the software-based methods, single image-based methods are simple, faster, cheaper, user-friendly and adaptable. Use of texture features for image analysis and classification is an important field in machine vision applications. Due to the fact that live and spoof fingerprints exhibit different textural properties, the proposed methods with several texture features from the literature have offered significant improvement in liveness detection accuracy. This paper presents a review on the existing texture features-based fingerprint liveness detection methods.

Keywords Biometrics · Spoof attack · Fingerprint liveness detection · Texture features

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1 Introduction

Biometrics refers to an automated individual identification using a certain physiological or behavioral trait [1]. Fingerprint is the oldest, mature and most commonly used biometric because of uniqueness, permanence and ease of use [2]. In the last two decades, fingerprint systems have been widely and incrementally used for security and commercial applications. It was demonstrated that these systems are susceptible to spoof attacks where an artificial replica of a live finger allowed illegitimate entry into the system [3]. The attacks created the awareness to secure the fingerprint systems by incorporating liveness detection, to detect whether the captured fingerprint image is from a live finger or an artificial finger.

A fingerprint consists of a specific arrangement of ridges and valleys of fingertip area. A live finger is characterized by the presence of pores (diameter 80–200 μm) along the ridges through which sweat is released due to perspiration process. The pores are somewhat circular in shape and can be open or closed. Open pores appear bright, and closed pores appear dark in the captured live fingerprint images. Locations, distribution and appearance of pores in a live fingerprint are different from those in a spoof fingerprint. The sweat from the pores travels along and across the ridges changing the wetness of these regions. The wet regions appear dark, whereas dry regions appear bright, in the captured fingerprints. The perspiration phenomenon does not occur in artificial fingers due to which gray-level distribution of a spoof fingerprint is different from that of a live fingerprint.

Spoof fingers can be fabricated with the user consent (consensual method), from latent fingerprint of the user (non-consensual method), or using synthetic fingerprint generator. A spoof finger is fabricated by pressing a finger into a soft material to create a mold, which is then filled with a material like gelatin, silicone or latex.

A fingerprint recognition system, categorized as an image processing system, consisting of sensor, feature extractor and matcher modules, identifies specific patterns in the input images. A liveness detection capability is integrated into fingerprint recognition systems to prevent an adversary from entering the system fraudulently. Recently, an exhaustive survey on fingerprint liveness detection techniques appeared in [4]. Hardware approaches include an additional hardware at the sensor level to detect liveness from biological or physiological signals such as temperature, odor, pulse oximetry [5–7]. S. Shuckers [8] pointed out that hardware methods based on live finger properties can be fooled by using spoof fingerprints created with properties similar to those of live fingerprints. Software-based methods are widely researched in the last few years. These methods use additional signal processing techniques for liveness detection. They are user-friendly, noninvasive and flexible. In dynamic features-based software methods, multiple images, separated by 2 or 5 s, of the same finger, are acquired to detect the changes in fingerprint image properties due to perspiration [9, 10], or skin deformation [11, 12], which can occur only in a live finger. The change is quantified using appropriately designed metrics to distinguish live fingers from spoof. Performance of these methods depends on the pressure of the presented finger, environmental conditions, user skills and material used in spoof finger fabrication. Static features-based software methods process the information from a single fingerprint image. These are classified into perspiration-based [13], pore-based [14], quality-based [15] and texture-based [16] methods. Perspiration-based methods use signal processing techniques to quantify perspiration phenomenon for liveness detection. However, the dynamic process of perspiration cannot be accurately captured by a single image. Pore-based methods count the number of pores for liveness detection. Requirement of high-resolution images (1000 dpi) to detect pores makes the method unsuitable for general-purpose applications. Quality-based methods define measures like ridge strength, clarity and continuity to detect quality from structural and statistical properties of images to differentiate between live and spoof fingerprints. Nowadays, a large number of liveness detection methods use texture features.

A fingerprint is characterized by abundant and strong textural information. The textural properties of a live fingertip surface are dependent upon skin elasticity, pore distribution and perspiration phenomenon. As a result, the pixels along and around the ridges of a live fingerprint exhibit wide and random variations in gray-level values. The material and physical characteristics of spoof fingers are constant. The live and spoof fingerprints differ in ridge width, inter-ridge distances, ridge frequency and gray-level distribution [16]. Therefore, texture features-based methods which can capture these variations from fingerprint image properties are expected to perform better.

The purpose of this work is to focus on the existing methods that use texture features to detect liveness in the presented fingerprints.

Section 2 contains brief discussion on the existing texture features-based fingerprint liveness detection methods followed by conclusion and reference sections, respectively.

2 Texture Features-Based Fingerprint Liveness Detection Methods

Spatial domain pixel intensity value variations create texture patterns in an image. One of the applications of image texture is image analysis using texture properties. The existing texture features-based fingerprint liveness detection methods are grouped into following categories:

2.1. Global texture features
2.2. Local texture features
2.3. Hybrid (global and local) texture features

2.1 Global Texture Features-Based Methods

Global texture features are computed over the entire image to represent it in a compact form. They essentially capture macrostructures in an image. Any standard classifier can be used due to compact feature size. Existing global texture features-based fingerprint liveness detection methods are described below-

Fingertip Surface Texture Coarseness

Compared to live fingers, the surface texture of spoof fingers is coarse due to synthetic material properties. Moon et al. [17] used high-resolution (1000 dpi) images of fingerprints to capture the coarseness. They used a wavelet-based image denoising method to eliminate the coarseness. The difference between the original image and the denoised image is high for spoof fingerprints due to large pixel value fluctuations in a coarse texture compared to live images of smooth texture. They used standard deviation as a metric to quantify this difference.

Power Spectrum Features

Though ridge-valley periodicity is not altered in a spoof finger fabrication process, some microcharacteristics, responsible for high-frequency features, are less defined due to roughness of the material and the increase in the ridgelines thickness. This results in loss of high-frequency details in a spoof fingerprint, whereas the power spectrum of a live fingerprint image exhibits significant high-frequency characteristics. Coli et al. [18] differentiated live and spoof fingerprints based on the power spectrum magnitude computed over the defined region of high frequencies.

A two-dimensional discrete Fourier transform of a fingerprint image produces two concentric rings around the origin. Jin et al. [19] used magnitude of energy in the inside ring, outside ring and the entire image energy, to differentiate between live and spoof fingerprints. A live fingerprint is characterized by high energy in the inside and outside ring due to clear ridge-valley structure. The method offered better classification accuracy compared to the existing dynamic features-based methods.

Spatial Domain Texture Features

Marasco and Sansone [20] used multiple texture features, pore spacing along the ridges, surface coarseness, first-order statistical texture features and gray-level intensity ratios, computed over the entire image, to test the classification accuracy on LivDet 2009 database [21]. The authors reported that the classification performance was different for each sensor for each texture feature.

Multiscale Transform Subband Energy Feature

Nikam and Agarwal performed classification on MNIT database [4] using feature vector consisting of energies of multiscale high-frequency subbands of wavelet transform [22], curvelet transform [23] and contourlet transform [24]. Multiple classifiers were used individually and in cascade. Contourlet and curvelet transform capture curve features well and offered better results than wavelet. However, for LivDet2011 database [25], the performance was not satisfactory [26].

Summary

Surface coarseness detection using wavelet denoising may help to reduce sensor-induced noise required for sensor independent evaluation at the cost of high-resolution systems. Fourier domain presents rich information about the signal. Particularly, phase information can be captured using complex transforms to distinguish between live and spoof finger textures. Fusion of global texture features reported better but variable performance for different sensors. It indicates that some features specific to an individual sensor are not captured by global features. Multiscale transform subband coefficients convey information about saliency in the images which corresponds to texture information. Appropriate features extracted from these coefficients may improve the classification accuracy.

2.2 Local Texture Features-Based Methods

Recently, fingerprint liveness detection methods using local texture features that are investigated in a variety of machine vision applications, are increasingly explored. Local texture features are derived by processing small patches of images and are represented by histogram of features. Some form of high-pass filtering is performed over image patches to capture local microtextures to improve discrimination capability compared to global features. Local features suffer from high dimensionality. Many of them have the advantages of rotation and illumination invariance. Existing local texture features-based fingerprint liveness detection methods are described below-

Local Binary Patterns

Use of local texture feature, Local Binary Pattern (LBP), was proposed by Nikam and Agarwal [27]. The LBP operator encodes the gray-level differences between the central pixel and the surrounding pixels over the defined region to assign a label to each image pixel. The histogram of all the labels constitutes the feature vector. LBP features capture coarseness and orientation of microtextures present in a fingerprint image. LBP performance was superior compared to the contemporary methods for a limited database. Experimentation on LivDet2011 database [25] reported different classification accuracy for each sensor and each type of spoof material [26].

X. Jia et al. [28] proposed Multiscale Block local Ternary Pattern [29] based on the difference between a central pixel and the average of a block to reduce sensitivity to noise. Unlike LBP, the ternary patterns reflect the difference between selected pixels and threshold. Experiments on LivDet2011 database [25] reported the lowest classification error among the methods considered. The same authors in [30] proposed two types of Multiscale Local Binary Patterns to take into account large-scale dependencies in spatial domain. In the first type, the radius of the LBP operator was increased to collect intensity information from a large area by using a Gaussian low-pass filter. In the second type, they applied a set of mean filters to the image. The comparison between pixels in the original LBP was replaced by the comparison between average values of pixels in each subregion. Experimental results on LivDet2011 database [25] reported lowest classification error rate for Biometrika, Digital Persona and Sagem sensors, while higher error rate for Italdata sensor.

Local Phase Quantization (*LPQ*)

Ghiani et al. [31] proposed LPQ, based on the finding that live and spoof finger images exhibit different frequency domain characteristics [18]. In frequency domain, phase represents many important features of a signal compared to amplitude. LPQ feature vector is constructed from de-correlated and quantized phase of four low-frequency discrete Fourier transform coefficients computed at each pixel of image using windowing technique. Histogram of LPQ feature vectors computed for the entire image compactly represents the image. LPQ, proposed for texture classification, is insensitive to image blurring and illumination variations as only phase information is used. Performance of LPQ was similar to that of LBP, but LPQ and LBP concatenated together offered significantly low error rate for all sensors, indicating they complement each other. LPQ is insensitive to small blur, but its performance drops for large amount of blur [32]. This suggests performance of LPQ depends on spoof material.

Binarized Statistical Image Feature (*BSIF*)

LBP and LPQ use heuristically designed filters to compute the features. Ghiani et al. [33] proposed BSIF features generated using filters that are designed from a large number of natural images to extract meaningful information from data. Learning-based methods allow flexibility in filter design with respect to descriptor length and image characteristics. The thresholded and binarized response of each filter computes a bit in BSIF code of the image. Different filter is used for each bit. The histogram of pixel BSIF code values represents the image. Experiments on LivDet2011 database [25] reported significantly low error rate for all the four sensors compared to LBP and LPQ but at the cost of large feature dimension.

Weber Local Descriptor (*WLD*)

Gragnaniello et al. [34] proposed WLD texture feature which consists of two components to represent contrast and orientation, respectively. Contrast is represented by the ratio of differences between central pixel and the surrounding pixel values to the central pixel value. The orientation is represented by the gradient computed at the current pixel location. Both the components are encoded to reduce feature dimension and capture high-frequency details. By concatenating the two components, a 2-D histogram is constructed to represent the image. Experimental results on LivDet2011 database [25] reported higher error rate compared to LBP and LPQ. Concatenation of WLD with LBP and LPQ offered superior results.

Improvement in the results can be achieved with the increase in code length at the cost of high feature dimension.

Wavelet Markov Local Descriptor (*WMLD*)

Gragnaniello et al. proposed WMLD [35] texture feature, based on Markov features, generated from transition probability matrices, to capture joint dependencies among wavelet coefficients across position, scale and orientation. Original image is decomposed to generate 13 subbands including the original image. Residue of each subband coefficient is obtained by subtracting predicted value from original value to capture local deviation due to image characteristics. Multiple Markov features constructed from transition probability matrices of residue coefficients capture dependency among wavelet coefficients to characterize microtextures. Experiments conducted on LivDet 2009 database [21] reported the lowest classification error for Crossmatch and Identix sensors. Orientation features were reported to have highest discrimination capability.

Histogram of Invariant Gradients (*HIG*)

Gottschlich et al. [36] proposed a gradient-based texture feature, HIG. Image was divided into circular regions of 16 pixels radius around the detected minutiae. Alternatively, the image can be divided into subblocks. For each identified local region, a histogram is constructed which counts occurrences of gradient orientation and magnitude. All computed local histograms constitute image feature. Experiments on LivDet2013 database [37] reported average classification accuracy similar to the winner of LivDet 2013 competition winner for Biometrika, Italdata and Swipe sensors and improved results for Crossmatch sensor.

Local Contrast Phase Descriptor (*LCPD*)

Gragnaniello et al. [38] proposed LCPD, which describes both spatial and frequency domain features to increase discrimination capability. In [31], performance of LPQ feature alone was worse and improved jointly with LBP and WLD. Local phase information captured by LPQ is complemented by concatenating with a modified differential excitation component of WLD. Instead of using a high-pass filter, Laplacian of Gaussian was used to construct differential excitation component. The infinite range of differential excitation ratio was encoded into finite values using nonlinear quantization. Experimental results on LivDet 2011 database [25] reported lowest overall average classification error.

Local Processing Using Ridgelet Transform

Nikam and Agarwal [39] proposed ridgelet transform, better at detecting line singularities than wavelet transform, for liveness detection. Image is partitioned into blocks; ridgelet transform is applied to each block. Energy and texture features derived from subband coefficients were tested individually on MNIT [4] database. Results were poor than wavelet transform-based results. As transform is applied locally, we classified the method as local feature based.

Summary

Local texture features have shown promising results, but their performance varies with sensor and spoof finger material. Fusion of multiple features has improved error rate and can be explored further. Increasing the support of local features has shown improvement in results as information is captured over large area.

2.3 Hybrid-Global and Local-Texture Features-Based Methods

Global features and local features capture different image characteristics because the support over which features are computed varies. Global features capture macro-textures, whereas local features capture local microtextures. Combined use of both is likely to improve the classification performance. However, the features need to be used judiciously to ensure improvement in the performance. The feature dimensionality needs to be taken care of. Use of both features is likely to improve fingerprint liveness detection accuracy and efficiency. The existing methods in this group are described below-

Multiscale Transform Subband-Based Local Texture Features

Nikam and Agarwal [27] proposed wavelet subband energy feature concatenated with Local Binary Pattern histogram features for fingerprint liveness detection. Wavelets capture image characteristics at multiple scales, and LBP captures fine microtextures. Experimental results on MNIT database [4] reported higher classification accuracy rate than the contemporary methods. However, the results in [26] on LivDet2011 database [25] reported relatively poor performance. Curvelet transform captures line and curve singularities better than wavelet transform. The same authors in [23] proposed curvelet transform and the gray-level co-occurrence matrix of subbands coefficients to generate texture features. Experimental results reported better classification accuracy than wavelet transform but poor performance compared to other methods [26]. In [24] texture features derived from gray-level co-occurrence matrix of contourlet transform subbands coefficients reported classification rate better than wavelet transform but almost same as curvelet transform.

Spatial Surface Coarseness Analysis (*SSCA*)

Periera et al. [40] complemented fingerprint coarseness computed at global level with local spatial information for images of 500 dpi resolution, followed in common commercial scanners, circumventing the need for high-resolution images in [17]. The residual noise image is divided into number of partitions. As the coarseness of each partition varies, the standard deviation of each partition is computed to produce deviation map. Deviation map is divided into sections; the histograms of all sections concatenated together represent the image feature. Experimental results on LivDet2011 database [25] conducted only for Sagem sensor show significant improvement over [17] but almost the same as offered by LivDet2011 competition winner.

Summary

A fingerprint image contains information from coarse to fine scales. An appropriate combination of global and local features using techniques that match fingerprint signal characteristics are likely to offer the desired results.

3 Conclusion

Fingerprint images of live and spoof fingers possess different textural characteristics. Single image-based software methods using local texture features have reported promising capabilities and results. Some of them are computationally intensive and have high feature dimensionality. They cannot capture gradual variations in the signal as computations are local. Global texture features-based methods are computationally economical, have compact feature size but fail to capture fine variations in the signal. It is desirable to have a liveness detection method whose performance is independent of sensor and spoof finger material with low spoof finger acceptance rate as well as low live finger rejection rate. Appropriate fusion of global and local features can provide more information to achieve the desired results.

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