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ESPYING THE LIVE FINGERPRINT FROM SINGLE IMAGE USING LOW LEVEL FEATURES AND SHAPE ANALYSIS

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Abstract— ***Fingerprint-based authentication systems have developed rapidly in the recent years. However, current fingerprint-based biometric systems are vulnerable to spoofing attacks. Moreover, single feature-based static approach does not perform equally over different fingerprint sensors and spoofing materials. In this paper, we propose a static software approach.We propose to combine low-level gradient features from speeded-up robust features, pyramid extension of the histograms of oriented gradient and texture features from Gabor wavelet using dynamic score level integration. We extract these features from a single fingerprint image to overcome the issues faced in dynamic software approaches, which require user cooperation and longer computational time. A experimental analysis done on LivDet 2011 data produced an average equal error rate (EER)of 3.95% over four databases. The result outperforms the existing best average EER of 9.625%. We also performed experiments with LivDet 2013 database and achieved an average classification error rate of 2.27% in comparison with 12.87% obtained by the LivDet 2013 competition winner.***

Keywords— ***Fingerprint liveness, low level features, Gabor filters.***

I. INTRODUCTION

Fingerprint liveness detection has been an active research topic over the last several years. It has been proven that it is possible to spoof standard optical and capacitive sensors .The possibility to spoof a fingerprint based authentication system creates the need to develop a method which can distinguish between live and fake fingerprint images. Both hardware and software based approaches can be used to solve this problem. However, hardware based approaches require additional devices to measure finger temperature, odor, pulse, oxiometry, etc. In addition, hardware based approaches are typically costlier due to the additional sensors required; beside, they require an end user to interact with the extra hardware. On the other hand, software based approaches do not employ additional invasive biometric measurements. However, these approaches are more challenging as they require the identification of discriminative features to differentiate between fake and live fingerprint images. Software based approaches are further divided broadly into dynamic and static based approaches. Dynamic software based approaches require a minimum of two time series images resulting in additional computational time.

1.1 Pore Based Approach

Manivanan et. al. [1 -5] provided an analysis of sweat pores to detect the liveness of the fingerprint.A high resolution sensor (greater than 800 dpi) was used to capture active sweat pores. High pass filtering was used to extract sweat pores and a correlation filter was used to extract the position of pores

Choi et. al. [6 - 12] used individual sweat pores spacing and distance to differentiate between the live and fake fingers. For data collection, user co-operation for drying their finger before scanning was required. According to the authors, the pore periodicity of a live finger can be detected more accurately when the finger is dry. An accuracy of 85% was obtained. However, in our opinion, the live finger of a person will not necessarily be dry as it might contain traces of moisture due to perspiration. Moreover, the authors only used one source of fake material (dental impression material) without considering other fake materials such as latex rubber and wood-glue which causes sweat pores to appear differently..First, confirm that you have the correct template for your paper size.

1.2 Combined Approach

Jia and Cai [35] proposed analyzing the time series image of the fingerprint to detect fake fingerprints. Five features from the image sequence were extracted, where two of them represent the skin elasticity, and the rest representing the physiological process of perspiration.

SVM was used as a classifier to discriminate between the live from the fake fingerprints.EER of 4.49% was obtained on the custom made database.10 image sequences were required for liveness detection which is time consuming. Besides, only

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gelatin was used for creation of the fake fingerprints. The template is used to format your paper and style the text

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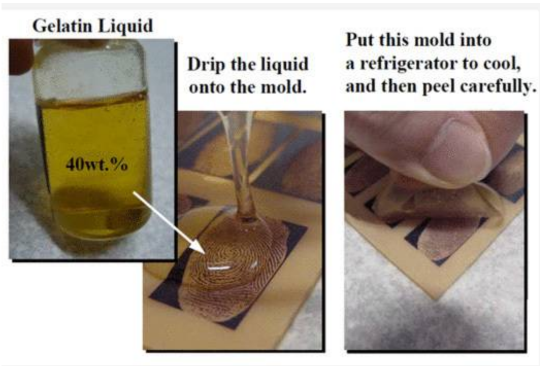
II. PROBLEM DEFNITION

There are many possible ways to fool a variety of fingerprint scanners using a well-duplicated synthetic finger made of silicone rubber, Gelatin, etc… in the biometric authentication systems.



III. PROPOSED METHOD

The system architecture is illustrated in this work, we divide the system into three main Sequential blocks:

• Image Pre-processing Stage
• Feature Extraction Stage
• Image Classification Stage

3.1 Image Pre-Processing Stage

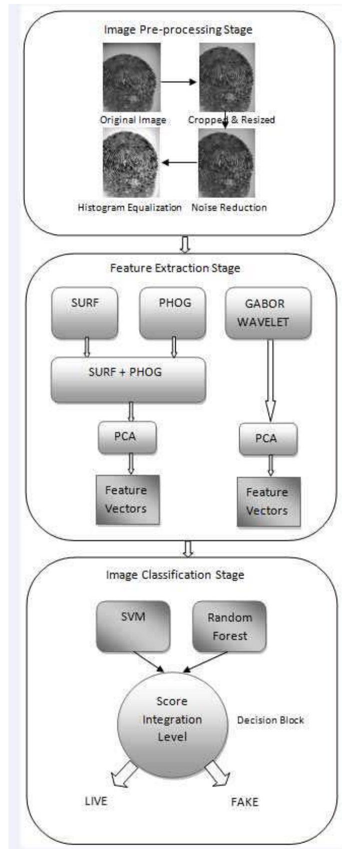
A poor quality fingerprint image is typically noisy, exhibits smudged line and has low contrasts between valleys and ridges. These effects can happen during image acquisition, due to dry or wet skin. Since the image acquisition stage is not always monitored for accepting only high quality images, fingerprint image enhancement and noise reduction are, therefore, important pre-processing factors in accurately detecting fingerprint liveness.

(a) Original image

(b) cropped image and resized

(c) after median filtering

(d)after histogram equalization



3.2 Feature Extraction Stage

In fingerprint authentication systems, the image is usually captured from multiple subjects using different scanners. Therefore, fingerprint images are typically found to be of different scales and rotations. In certain scenarios, the fingerprint images are partially captured due to human errors. In order to obtain features that are invariant to these problems, we use various features that capture properties of live fingerprint images.

In our work, we choose to use SURF as it is invariant to illumination, scale and rotation. SURF is also used because of its concise descriptor length. SURF shrinks the descriptor length to 64 floating point whereas standard SIFT implementation uses a descriptor consisting of 128 floating point values thus reducing computational time. While SURF is invariant to object orientation and scale transformation, it is not invariant to geometric transformations. Hence, in order to

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compensate the limitations of SURF, PHOG descriptors are used to extract local shape information to obtain more discriminative features. In addition, Gabor wavelet features are also incorporated for texture analysis.

SURF:

SURF is an in-plane rotation detector and descriptor. The detector locates the key points in the image and the descriptor describes the features of the key points to constructs the feature vectors of the key points. SURF then uses the determinant of the approximate Hessian-matrix on the integral image to locate the key feature points. For the key point descriptor, SURF uses the sum of the Haar wavelet responses to describe the feature of a key point. Haar wavelet computes the responses in x and y directions to describe the intensity distribution of a key point.

PHOG:

The local shape attributes are extracted and introduced using PHOG. HOG captures the intensity gradients and edge directions to describe the shape and appearance in an image.Good performance of PHOG in inspired us to use it for the fingerprint image liveness classification problem. In our proposed method, the image is divided into a spatial grid over all the pyramid levels. Sobel filter of 3×3 is applied to the edge contours for calculating the gradient angle and magnitude. Then the gradient is joined at the various pyramid level and histogram is calculated for each grid.

Gabor:

We also use Gabor Wavelet to extract features from fingerprint images for texture analysis. Gabor filters have optimal localization properties in both the frequency and spatial domain, and have been successfully used in many applications to extract discriminative features. In fingerprint images, the local ridge characteristics are extracted via a set of Gabor filters whose frequency corresponds to the inter-ridge spacing in fingerprints.

3.3 Image Classification Stage

In this section, we describe the dynamic score level integration algorithm for the purpose of selecting the best classifier during decision making.We performed experiments on the LivDet 2013 training datasets and the results are mentioned in Table II. For approximately 97% of the test samples, the prediction score above 0.6 and below 0.4 is a correct score for live and fake fingerprints.

IV. EXPERIMENTAL RESULT

Datasets: Our experiments were carried out on publicly available fingerprint liveness database for LivDet 2011 and 2013 competitions from Clarkson University - University of Cagliari. For the LivDet 2011 database, four optical sensors, Biometrika, Digital Persona, ItalData, and Sagem were used to collect the fingerprints. Similarly, four optical sensors, Biometrika, Digital Persona, ItalData, and Swipe were used to collect fingerprints for the LivDet 2013 database. The corresponding spoof materials were chosen from body double, latex, PlayDoh, wood glue, gelatine, latex, ecoflex and modasil.Highlight all author and affiliation lines.

Classifier Parameters: Select the Columns icon from the MS Word Standard toolbar and then select "1 Column" from the selection palette. For the SVM classifier, the linear kernel is selected for its computational efficiency and better performance over nonlinear kernels. For the RT classifier, the maximum number Of trees is 100, and the maximum depth for each tree is 15.

Results and Comparison: ACE = FLR + FFR/2

Methods	Biometrika	Digital	ItalData	Sagem	Avg. ACE
SURF	9.12	7.95	8.35	6.77	8.04
PHOG	22.45	13.07	20.05	16.1	17.92
Gabor	11.21	7.85	12.5	6.28	9.46
SURF+PHOG	8.76	6.9	7.4	6.23	7.32
Our Method	**7.89**	**6.25**	**8.1**	**5.36**	**6.9**
WLD+LPQ [47]	7.2	8.0	12.65	3.66	7.87
MBLTP [46]	10.0	6.9	16.3	5.9	9.77
multiresolution LBP [48]	10.8	7.1	16.6	6.4	10.22
Original LBP [49]	13.0	10.8	24.1	11.5	14.85
Tans method [50]	43.8	18.2	29.6	24.7	29.07
Power Spectrum [34]	30.6	27.1	42.8	31.5	33
Curvelet Energy [28]	45.2	21.9	47.9	28.5	35.87
Curvelet GLCM [28]	22.9	18.3	30.7	28.0	24.97
Wavelet Energy [18]	50.2	14.0	46.8	22.0	33.25
Ridges Wavelet [12]	38.8	27.5	56.9	20.5	35.92
Valleys Wavelet [27]	29.0	13.0	23.6	28.0	23.4
Dermalog [10]	20.0	36.1	21.8	13.8	22.92
Federico [10]	40.0	8.9	40.0	13.4	25.57
CASIA [10]	33.9	25.4	26.7	22.8	27.2

FLR (False Living Rate) represents the percentage of fake fingerprints misclassified as real and the False Fake Rate (FFR) represents the percentage of live fingerprints misclassified as fake. According to the rules of Livdet 2011 [13], the liveness of a testing fingerprint image is represented by a value between 0 and 100. The threshold value is set to be 50. The fingerprint image with value more than 50 is regarded as the real one, while it is considered fake if the value is less than or equal to 50. EER is computed as the point where FLR=FFR. Table IV provides the ACE comparison results with many existing solutions. It can be seen that the proposed solution outperforms other methods in terms of average ACE. In addition, the results obtained from our method are more consistent than compared to other methods. For example, the ACE values obtained by [14] vary from 3.66 to 12.6, while the proposed method yields a range from 5.36 to 8.1.

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V. CONCLUSION

In this paper, we proposed a novel method for fingerprint liveness detection by combining low level features, which includes gradient features from SURF, PHOG, and texture features from Gabor wavelet. In addition, an effective dynamic score level integration module is proposed to combine the result from the two individual classifiers. We carried out experiments on two most popularly used databases from LivDet competition 2011 and 2013. In depth comparison is done with the current state of the art, and the winner of LivDet 2011 and 2013 fingerprint liveness detection competition. ACE rate of 2.27% in comparison to the 12.87% of the 2013 LivDet competition winner is a significant performance gain. The proposed method scored consistently low EER over all the six sensors which were not observed in the state of the art methods.

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