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Enhancing Fingerprint Liveness Detection from Single Image Using Low-Level Features and Shape Analysis Using SURF and PHOG Algorithm

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Abstract:
Fingerprint primarily based authentication systems have developed rapidly within the recent years. However, current fingerprint based biometric systems square measure susceptible to spoofing attacks. Moreover, single feature primarily based static approach doesn't perform equally over completely different fingerprint sensors and spoofing materials. In this paper, tend to propose a static software system approach. We propose to combine low level gradient options from Speeded-Up robust Features (SURF), pyramid extension of the Histograms of oriented Gradient (PHOG) and texture options from gabor wavelet using dynamic score level integration tend to extract these options from one fingerprint image to beat the problems baby-faced in dynamic package approaches that need user cooperation and longer machine time.

I. INTRODUCTION

BIOMETRIC based authentication systems are getting more common in the security domain. Much research has been done in this field in recent years. The advantage of using biometrics for authentication purpose comes from the unique features of each individual [2]. Iris and fingerprints are unique for every human. In addition, they are simple and difficult to copy. When compared to password based systems, biometrics can neither be easily hacked, nor be visually seen and remembered. Thus, fingerprint based authentication systems are becoming increasingly common these days. However, due to the excessive use of fingerprint security systems, they have become a target of attacks. Fingerprint liveness detection has been an active research topic over the last several years [3]. It has been proven that itis possible to spoof standard optical and capacitive sensors [4]. 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.

However, hardware based approaches require additional devices to measure finger temperature [6], odor [7], pulse [8], oxiometry [8], 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 [9]. 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.

In a static software based approach, a user is only required to place his/her finger on the sensor for a short duration in an undedicated way for a single image capture. Most of the works in fingerprint liveness detection use a single feature based approach. For example, the works in [1] and [10] engineer's the feature extracted from a specific material for detecting fake fingerprint.. Furthermore, it is not practical for the authentication system to have prior knowledge of the types of material used to create the fake fingerprint in real world scenarios.

In this paper, we propose a method to overcome the limitations faced in the static software based approaches where a single feature set fails to perform equally over different fingerprint sensors and materials. Our methodology extracts low level textural and gradient information for fingerprint liveness detection from a single image. We propose the use of SURF features in combination with PHOG to obtain gradient features that discriminate well between fake and live fingerprint images. SURF features have a concise descriptor length which is compact and takes less computational time as compared to LBP. In addition, SURF is also invariant to scale and image rotation.

Unlike, LivDet 2013 competition winner and other top four teams which do not perform well on Crossmatch sensor, our method performs exceedingly well on Crossmatch In an extensive experiment is conducted and the results are compared with the current state of the art [1].

II. PREVIOUS WORK

In the literature in the field of software based fingerprint liveness detection. Since our proposed method focuses on software based approaches we refer the reader to [7]–[9] for hardware based approaches. Software based approaches extract intrinsic properties directly from the fingerprint images which are acquired by the sensor. Currently, the majority of software based approaches depends on the analysis of the skin perspiration through the pores [11]–[13], skin deformation [14]–[16] and image quality [3], [17]–[21]. Software based approaches are further subdivided into dynamic software-based and static software-based.

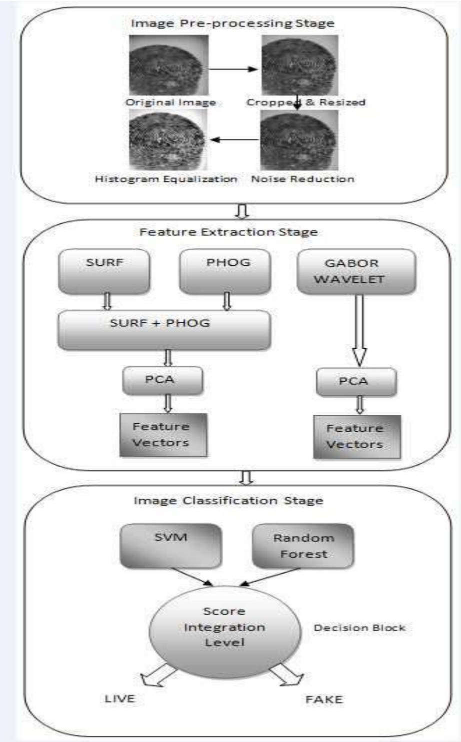

Fig .1 Different process

A. Dynamic Software-Based Approach

In dynamic software-based approach, features are extracted from multiple frames of the same finger. The evolution of features over time captures the vital information which is exploited in this approach. Dynamic software based approach can be further divided into two categories: skin deformation based approach and perspiration based approach.

1) Skin Deformation Based Approach: Zhang et. al. [14] proposed a method which is based on fingerprint deformation. Authors introduced a new method called the thin-plate spline (TPS) model. A user is asked to apply pressure in four directions to measure minutiae distances between the distorted fingerprints with undistorted fingerprint. Fingerprints. Similar to the cases of [14] and [15], this method also requires user cooperation for capturing the fingerprints.
This method obtained an EER of 4.78% over a self-created database.

2) Perspiration Based Approach*:* Derakhshani et al. [11] proposed a method based on the perspiration phenomenon. Two fingerprint images are captured at different intervals and the middle ridge signals extracted from them are compared.

They then use a back-propagation neural network classifier to differentiate between the live and fake fingerprint. The limitation of this system is that it requires a special kind of DC capacitance-based Si CMOS fingerprint scanner and is time consuming to capture the images at intervals. In addition, the result of 100% precision was achieved over a limited dataset of 18 live, 18 spoofs and 18 cadaver fingerprints. Abhyankar 0 and 2 sec. This method achieved an EER of 0.03%. Nikam and Agarwal [13] proposed a system based on the ridgelet transform which needs only one fingerprint to detect liveness. Authors reported that ridgelet transform singularities along the line in a more efficient way than wavelets.

B. Static Software Based Approach:

In static software based approach, features are exploited from a single fingerprint to overcome the drawbacks of high computational time and user cooperation required in dynamic software based approaches. Generally, static measurements are well captured from a higher resolution sensor (1000 dpi and above), but the common sensors are generally in the range of 500 dpi.

1) Image Quality Based Approach:

Introduce a novel fake fingerprint detection methodology using multiple static image features. Histogram, power spectrum, directional contrast, ridge signal, and ridge thickness of fingerprint image were considered as representative static features.

During this phase, the energy of the fingerprints was identified. In general, the energy of the live fingerprint is greater than the energy of the fake fingerprint. It is the energy difference that is used as the indicator for fake fingerprint detection. For this method, an ERR of 11.4% was achieved. Ghiani et. al. [3] proposed a novel fingerprint liveness descriptor named Binarized Statistical Image Features (BSIF) which encodes the local fingerprint texture on a feature vectors pores, the number of sweat pores would differ. Difference in number was used as a basis for fingerprint liveness detection. An accuracy of 14.75% was achieved over a self-created database using the CrossMatch Technologies.

C. Combined Approach

In this approach, EER of 4.49% was obtained on the custom made database. It was illustrated that the combination of perspiration features and textural features produces better result. Similar to the limitation of a perspiration based approach, this method also requires more than one fingerprint image. An overall accuracy rate of 74.4% was achieved over three sensors (Biometrika, Crossmatch and Identix) used in LivDet 2009 competition.

III. PROPOSED METHOD

As illustrated in Fig. 1, we observe that it is very difficult to visually differentiate between live and fake fingerprints. Although the difference in the pixel intensity of the gray-scale of the live and fake fingerprints image is difficult to perceive, this difference can be measured by calculating the mean and standard deviation values of the gray level image. Also, based on visual observation, there are more sweat pores in the live fingerprint as compared to the fake fingerprint images. Inspired by these minute differences, we design low level features that are able to represent discriminating characteristics between live and fake fingerprints. The system architecture is illustrated in Fig. 1. In this work, we divide the system into three main sequential blocks:

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

*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.

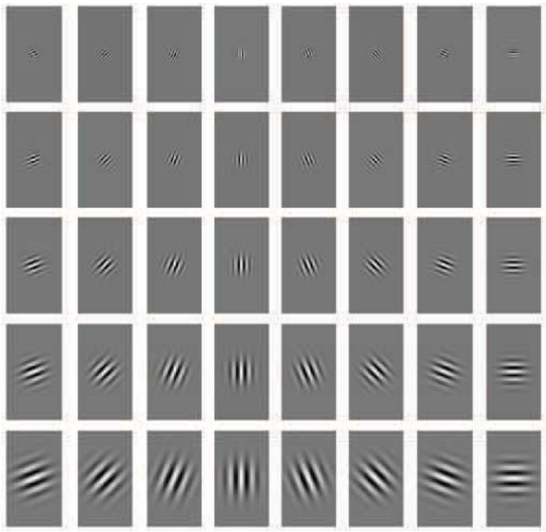

Fig.2 Pre-processing stage

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. We enhanced the quality of the image by first cropping the fingerprint region in the image and then performing histogram equalization to increase the perception information. The Canny edge detector [is first applied for the purpose of identifying the biggest contour in order to find the extreme ridge contours. Specifically, we remove the non-relevant white region found in the borders prior to cropping the region of interest shown in Fig. 3(a). In order to remove noise captured during image acquisition, median filtering is then applied on the cropped images without reducing the sharpness of the input image as shown in Fig. 3(b). Finally, histogram equalization is performed to improve the contrast in the image by diversifying the intensity range over the whole cropped image as shown in Fig. 3(a). The output achieved after this stage is an image with a reduced noise and improved definition of the ridge structure.

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 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. Details of the above features are provided in the following content.

a) 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. SURF has been proven to be distinctive and robust in representing local image information. Since SURF represents images using local features, it works well with occluded and partial fingerprint images . For detailed description about SURF, we direct the readers to.

b) 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.

The Gabor wavelets (kernels, filters) can be defined as follows: where μ and υ define the orientation and scale of the Gabor frequency, and is the spacing factor between kernels in the frequency domain. The Gabor kernels in are all self similar since they can be generated from one filter, the mother wavelet, by scaling and rotation via the wave vector $k_{\mu,\upsilon}$. Each kernel is a product of a Gaussian envelope and a *complex plane wave, while the first term in the square brackets in determines the oscillatory part of the kernel and the second term compensates for the DC value. The effect of the DC term becomes negligible when the parameter, which determines the ratio of the Gaussian window width to wavelength, has sufficiently large values. Shows the real part of the Gabor kernels for a sample image at five scales and eight orientations. The following parameters of Gabor2) were used. Fig.4(a). The real part of Gabor functions for five different scales and eight different orientations.

The kernels exhibit desirable characteristics of spatial frequency, spatial locality, and orientation selectivity. The Gabor wavelet representation of an image is the convolution of the image with a family of Gabor kernels as defined by (1). Let $I(x, y)$ be the gray level distribution of an image, the convolution of image I and a Gabor kernel $\psi_{\mu,\nu}$ is defined as follows : $I(z)$.
Applying the convolution theorem, we can derive each $O_{\mu,\nu}(z)$ from (3) via the Fast Fourier Transform (FFT).

d) Feature reduction stage: While we have identified key features to categorize live and fake fingerprint images the resulting dimensionality of the data set is too large. Therefore, Principal Component Analysis (PCA) is applied to both GABOR and SURF+PHOG feature vectors in order to reduce its dimensionality. PCA is a statistical analysis method to extract the main contradiction of features.

This is done to make sure that the information from the testing dataset does not leak into the training database and dilute the generalization. Moreover, the comparison has to be done on the same Due to these factors, we select SVM for SURF+PHOG features and RT for Gabor features.

3) Image Classification Stage:

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. For approximately 97% of the test samples, the prediction score above 0.6 and development purposes. After training the two different classifiers, the results are generated using the unseen development set. The results are subsequently compared with their correct labels to decide the higher scoring classifier. The best scoring classifier is noted for that particular dataset and it is used as a starting selection point in our decision making module as illustrated in the performance of classifiers on the different sensors. Since we already know the high scoring classifier, we choose the initial prediction answer from the high scoring Fig. 4(b), Histogram plot to select upper and lower bound for decision making in dynamic score level decision module using LivDet 2013 training dataset. (a) Bioemtrika. (b) Italdata. (c) Crossmatch. (d) Swipe. classifier observed during the experiments.For instance, if SURF+PHOG based trained classifier performs better than Gabor based trained classifier, then we choose the starting prediction from the former. Next, we take the absolute difference

IV.Output result:

Fig.3(a) Input Image

Fig.3(b) Noise Removed Image

Fig.3(c) Fake Finger Print

Fig.4(a) Input Image

Fig4.(b) .Noise Removed Image

Fig.4(c) Original Finger Print

V.CONCLUSION

In this paper, we proposed a novel method for finger print 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

REFERENCES:

[1] L.Ghiani, D. Yambay, V. Mura, S. Tocco, G.L. Marcialis, F. Roli, andS. Schuckcrs, “Livdet 2013 fingerprint liveness detection competition 2013,” in *Biometrics (ICB), 2013 International Conference on*, June 2013, pp. 1–6.

[2] A.K. Jain, “Next generation biometrics,” in *Department of Computer Science & Engineering, Michigan StateUniversity,Department of Brain & Cognitive Engineering, Korea University*, 10 Dec 2009.

[3] L. Ghiani, A. Hadid, G.L. Marcialis, and F. Roli, “Fingerprint liveness detection using binarized statistical image features,” in *Biometrics:Theory, Applications and*

Systems (BTAS), 2013 IEEE Sixth InternationalConference on, Sept 2013, pp. 1–6.

[4] S.T.V. Parthasaradhi, R. Derakhshani, L.A. Hornak, and S. A C Schuckers, “Time-series detection of perspiration as a liveness test in fingerprint devices,” *Systems, Man, and Cybernetics, Part C: Applications andReviews, IEEE Transactions on*, vol. 35, no. 3, pp. 335–343, Aug 2005.

[5] MojtabaSepasian, Cristinel Mares, and WamadevaBalachandran, “Livenessand spoofing in fingerprint identification: Issues and challenges,” in *Proceedings of the 4th WSEAS International Conference on ComputerEngineering and Applications*, Stevens Point, Wisconsin, USA, 2009, CEA’10, pp. 150–158, World Scientific and Engineering Academy and Society (WSEAS).

[6] M. Sandstrom, “Liveness detection in f aingerprint recognition systems, master thesis, http://www.ep.liu.se/exjobb/isy/2004/3557/exjobb.pdf,” .

[7] Denis Baldisserra, Annalisa Franco, Dario Maio, and DavideMaltoni, “Fake fingerprint detection by odor analysis,” in *Advances in Biometrics*, David Zhang and AnilK. Jain, Eds., vol. 3832 of *Lecture Notes inComputer Science*, pp. 265–272. Springer Berlin Heidelberg, 2005.

[8] P.V. Reddy, A. Kumar, S. Rahman, and T.S. Mundra, “A new antispoofing approach for biometric devices,” *Biomedical Circuits and Systems, IEEE Transactions on*, vol. 2, no. 4, pp. 328–337, Dec 2008.

[9] Stephanie A. C. Schuckers, Stephanie A. C. Schuckers, Ph. D, and Ph. D, “Spoofing and anti-spoofing measures,” *Information Security TechnicalReport*, vol. 7, pp. 56–62, 2002.

[10] D. Yambay, L. Ghiani, P. Denti, G.L. Marcialis, F. Roli, and S. Schuckers, “Livdet 2011; fingerprint livenessdetection competition 2011,” in *Biometrics (ICB), 2012 5th IAPR International Conference on*, March2012, pp. 208–215.

[11] Reza Derakhshani, Stephanie A.C. Schuckers, Larry A. Hornak, and Lawrence O’Gorman, “Determination of vitality from a non-invasive biomedical measurement for use in fingerprint scanners,” *PatternRecognition*, vol. 36, no. 2, pp. 383 – 396, 2003, Biometrics.

[12] Bozhao Tan and S. Schuckers, “Liveness detection for fingerprint scanners based on the statistics of wavelet signal processing,” in *Computer Vision and Pattern Recognition Workshop, 2006. CVPRW ’06.Conference on*, June 2006, pp. 26–26.

[13] Shankar BhausahebNikam and ASuneetaAgarwal, “Ridgelet-based fake fingerprint detection,” *Neurocomput.*, vol. 72, no. 10-12, pp. 2491–2506, June 2009.

[14] Yangyang Zhang, JieTian, Xinjian Chen, Xin Yang, and Peng Shi, “Fake finger detection based on thin-plate spline distortion model,” in *Advancesin Biometrics*, Seong-Whan Lee and StanZ. Li, Eds., vol. 4642 of *LectureNotes in Computer Science*, pp. 742–749. Springer Berlin Heidelberg, 2007.

[15] A. Antonelli, R. Cappelli, Dario Maio, and DavideMaltoni, “A new approach to fake finger detection based on skin distortion,” in *Proceedings of the 2006 International Conference on Advances in Biometrics*, Berlin, Heidelberg, 2006, ICB’06, pp. 221–228, Springer-Verlag.

[16] JiaJia, LianhongCai, Kaifu Zhang, and Dawei Chen, “A new approach to fake finger detection based on skin elasticity analysis,” in *Advances inBiometrics*, Seong-Whan Lee and StanZ. Li, Eds., vol. 4642 of *LectureNotes in Computer Science*, pp. 309–318. Springer Berlin Heidelberg,2007.

[17] Heeseung Choi, Raechoong Kang, Kyoungtaek Choi, AndrewTeohBeng Jin, and Jaihie Kim, “Fake-fingerprint detection usingmultiple static features,” *Optical Engineering*, vol. 48, no. 4, pp.047202–047202–13, 2009.

[18] S.B. Nikam and S. Agarwal, “Texture and wavelet-based spoof fingerprint detection for fingerprint biometric systems,” in *EmergingTrends in Engineering and Technology, ICETET ’08. First InternationalConference on*, July 2008, pp. 675–680.

[19] Y.S. Moon, J.S. Chen, K. C. Chan, K. So, and K. C. Woo, “Wavelet based fingerprint liveness detection,” *Electronics Letters*, vol. 41, no. 20, pp. 1112–1113, Sept 2005.

[20] A. Abhyankar and S. Schuckers, “Fingerprint liveness detection using local ridge frequencies and multiresolution texture analysis techniques,”in *Image Processing, IEEE International Conference on*, Oct 2006, pp. 321–324.

[21] Fingerprint Liveness Detection from Single ImageUsing Low-Level Features and Shape Analysis Rohit Kumar Dubey, Jonathan Goh, and Vrizlynn L. L. Thing