Fingerprint Spoof Detection Using Gradient Co-occurrence Matrix

Xin Liu and Yujia Jiang

***Abstract*—Fingerprint recognition systems have been increasingly deployed in many applications because of its uniqueness and convenience. However, this kind of system is threatened by spoof attacks as the fake fingerprint can be easily produced from gelatin, silicone, or other materials. In this paper, we proposed a software-based fingerprint spoof detection method by calculating co-occurrence matrix from the gradient magnitude and orientation. In the process of feature extraction, the gradient magnitude and orientation are firstly calculated, quantized, and truncated. Then, the co-occurrence of the magnitude and orientation is computed. In addition, we count the co-occurrence of magnitude and orientation at two adjacent pixels to achieve the improved detection accuracy. Two kinds of features are separately utilized to train support vector machine classifiers on three public databases in Fingerprint Liveness Detection Competition 2009, 2011, and 2013. The experimental results have demonstrated that the proposed method outperforms many previous fingerprint spoof detection methods.**

***Index Terms*—Biometrics; Fingerprint spoof detection; Co-occurrence Matrix; Image gradient.**

I. INTRODUCTION

FINGERPRINT recognition systems have been widely deployed in many applications [4, 5]. However, these systems are vulnerable to spoof attacks because fake fingers can be easily produced with cheap materials such as gelatin and silicon. The user's fingerprint may be peeped to make a spoof one for illegal authorization. Or a user may make a spoof fingerprint for himself to cheat the attendance system. It is important to solve this secure problem.

Fingerprint spoof detection (FSD) aims to detect whether a fingerprint image is captured from a spoof finger or not. There are two kinds of FSD methods, i.e., hardware-based and software-based methods. The hardware-based methods assemble hardware devices into the fingerprint system to detect the life signs of fingers such as pulse, conductivity, or blood pressure. The finger will be recognized as a spoof one once no such signs are found. The hardware-based methods require additional hardware equipment which increases the overall cost of the system. The software-based methods add spoof detection algorithm to the software structure in the existing systems. The software-based techniques detect the spoof fingers by analyzing the images obtained from the existing imaging sensors. It is less expensive and more flexible to future adoption [6-8]. In this paper, we proposed a software-based FSD method by calculating co-occurrence matrix of gradient magnitude and orientation.

The rest of the paper is organized as follows. Section II presents related works on the software-based FSD methods. Section III describes the feature extraction process. Experimental results are shown in Section IV. Conclusions are drawn in Section V.

II. RELATED WORKS

Early researchers designed many FSD methods by observing the differences of sweat pore [11-13], perspiration [2, 15], skin elasticity [17, 18], and image quality [20, 21] between live and spoof fingers. The effectiveness of these methods can be easily understood. But their detection accuracies need to be improved. Afterward, FSD methods based on textural features received more and more attentions. Abhyankar and Schuckers [23] developed a method based on multi-resolution texture features and local ridge frequency features. Their texture features include: 1) the first order features, i.e. energy, entropy, median, and variance of the histogram, and 2) the second order features, i.e. cluster shade and cluster prominence of the co-occurrence matrix. Coli et al. [25] claimed that the high-frequency details of the spoof fingerprint images were greatly reduced, and extracted features from the power spectrum for the classification. Nikam and Agarwal proposed several liveness detection methods based on the texture analysis of the fingerprint images. Nikam and Agarwal proposed several liveness detection methods based on the texture analysis of the fingerprint images. The authors extracted many distinguishable features through various texture measure methods such as, the Gabor filters [26], the curvelet transform [28, 29], the Ridgelet transform [9], the wavelet transform [32], and the gray-level co-occurrence matrices combined with the wavelet transform [33]. Ghiani *et al.* [35] calculated the local phase information (LPQ) from Fourier transform for the FSD problem. In 2013, Gragnaniello *et al.* [36] proposed an FSD method based on Weber Local Descriptor (WLD). The authors combined their WLD and LPQ features to achieve an improved detection accuracy. Gragnaniello *et al.* [37] designed the local contrast phase descriptor to deal with FSD problem. Authors extracted features from both the

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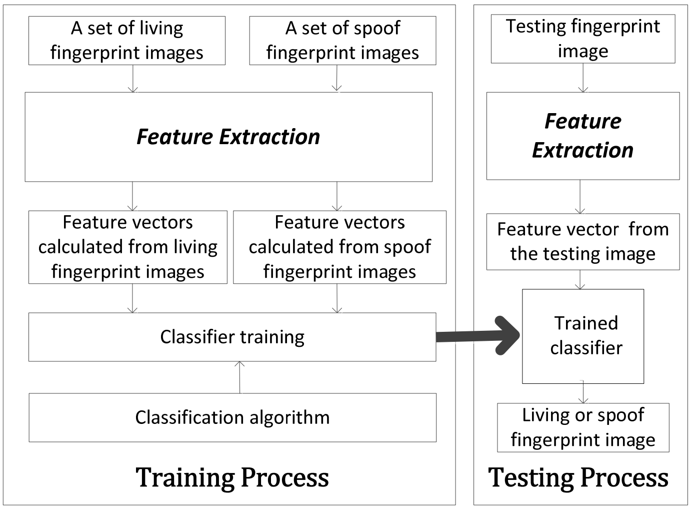

Fig. 1. The framework of the proposed fingerprint spoof detection method

spatial and frequency domains. Jia *et al.*[19] stated that the texture of fingerprint images could be characterized more adequately than the original LBP. Two multi-scale LBP descriptors are utilized to extract features for the FSD problem. Gottschlich *et al.* [30] calculated the histogram of gradient orientation from the fingerprint ridge. This method is robust and obtains the stable detection performances across the different databases. Xia *et al.* [38] calculated two kinds of texture features for the FSD problem. The second and third-order co-occurrence arrays were calculated with image differences. Dubey *et al.* [39] proposed an FSD method by combining the low-level gradient features, the histogram of gradient orientation, and the texture features from Gabor wavelet. This method performs well in the cross sensor scenario. Sasikala and Lakshmi prabha [40] proposed to apply feature selection to achieve an improved detection accuracy. Yuan *et al.* [41] calculated multi-scale LPQ and used principal component analysis to decrease the feature dimension. Kim [42] revealed that the spoof materials tended to yield the non-uniformity in the fingerprint images, and extract features by using the local coherence descriptor.

III. Feature Extraction

The fingerprint spoof detection is a typical two-class classification problem, i.e., classifying a pending fingerprint image into either a spoof or a live one. The framework of our method includes two parts: the training process and the testing process, as shown in Fig. 1. A classifier is trained using two classes of feature vectors in the training process. Then, the trained classifier is utilized to detect the fingerprint image. Feature extraction is a key step to deal with this classification problem.

In this paper, an 8-bit grayscale fingerprint image is denoted as a matrix $\mathbf{I} = \left(I_{i,j}\right) \in \{0,..,255\}^{m\times n}$, where $I_{i,j}$ represents the gray value of the pixel at position (i,j). There are two steps in our feature extraction process. Firstly, the image gradients are calculated for each image pixel. Secondly, the magnitudes and orientations of the image gradients are quantized and truncated. Thirdly, the co-occurrence matrix is construct from the processed magnitudes and orientations. Finally, the elements of the co-occurrence matrix are arranged as the feature vector to represent the fingerprint image itself.

A. Image Gradient

The image gradient represents the directional change in images and is quite useful to extract image texture information. Here, we use the filter templates $[-1\ 0\ 1]$ and $[-1\ 0\ 1]^T$ to calculate horizontal and vertical gradient of image:

$$\begin{cases} G_H(i,j) = I_{i,j-1} - I_{i,j+1}, \\ \quad \text{for } i \in \{1,\dots,m-2, j \in \{1,\dots,n-2\}, \\ G_V(i,j) = I_{i-1,j} - I_{i+1,j}, \\ \quad \text{for } i \in \{1,\dots,m-2, j \in \{1,\dots,n-2\}. \end{cases} \tag{1}$$

Then, the magnitude G_M and the orientation G_O of the gradient at position (i,j) are calculated as:

$$G_M(i,j) = \sqrt[2]{G_H(i,j)^2 + G_V(i,j)^2}, \tag{2}$$

$$G_O(i,j) = arctan\left(\frac{G_V(i,j)}{G_H(i,j)}\right). \tag{3}$$

B. Quantization and Truncation

The gradient magnitude and orientation need to be quantized to integers for calculating co-occurrence matrix. In order to obtain a compact and informative feature vector, the gradient magnitude should be limited to a proper range. Specifically, the gradient magnitude is quantized and truncated as:

$$G_M(i,j) \leftarrow Trunc_T\left(Round\left(\frac{G_M(i,j)}{Q}\right)\right), \tag{4}$$

where Q is the quantization step, the function $Round(x)$ rounds a decimal to its nearest integer, and $Trunc_T(x) =$

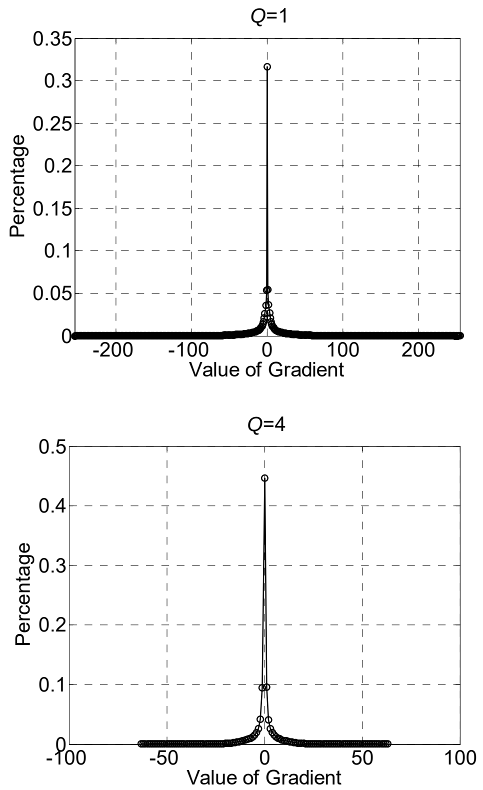

Fig. 2. Histogram of the gradients

$$\begin{cases} x, & if x \le T \\ T, & if\ x > T \end{cases}.$$

In this paper, the elements of the co-occurrence matrix will be used as features. The dimensionality of the feature vector is depended on the dynamic range of the differences. The histogram of the gradients has a sharp peak can can be approximated by Laplacian distribution as shown in Fig. 2. Thus, the gradients can be truncated to a small range $[-T, T]$ without losing much information. In addition, the quantization can further shrink the range of gradients, which further helps to reduce the dimensionality of the feature vector.

The gradient orientation has a definite range, thus needs no truncation, and can be quantized as:

$$G_O(i,j) \leftarrow Round\left(\frac{G_O(i,j)}{\pi/2} \times \theta\right). \quad (5)$$

In this way, we quantize the gradient orientation into the integer set of $\{-\theta, \dots, 0, \dots, \theta\}$.

C. Co-occurrence matrix

Co-occurrence matrix is a widely used tool to extract image features. Usually, the co-occurrence matrix is constructed on the gray values of the image and is typically large in dimensionality and sparse in non-zero elements. Thus, in order to extract a compact feature vector, the energy, entropy, contrast, and correlation of the co-occurrence matrix are often further calculated as features. In this paper, we construct the co-occurrence matrix from the gradient magnitude and orientation. Since the range of the both magnitude and orientation can be limited effectively by adjusting the quantization and truncation parameters, we directly use the matrix elements as the image features. In this paper, we try to calculate two kinds of co-occurrence matrix. The first one is to calculate the co-occurrence matrix from the gradient magnitude and orientation which are calculated from one pixel. The other is to calculate the co-occurrence matrix from two pairs of gradient magnitudes and orientations which are calculated from two adjacent pixels. Specifically, the two kinds of co-occurrence matrix are constructed as follows:

$$M_1(s,t) = \sum_{i=1}^{m-1} \sum_{j=1}^{n-1} \gamma(G_M(i,j), s) \times \gamma(G_O(i,j), t), \quad (6)$$

TABLE I
CHARACTERISTICS OF THE DATASETS USED IN LIVDET2009

DATASET		LivDet2009		
		Biometrika	Crossmatch	Identix
Model No.		FX2000	V300LC	DFR2100
Res.(dpi)		569	500	686
Image size		312×372	480×640	720×720
Training Samples	Live	520	1000	750
	Spoof	520	1000	750
Testing Samples	Live	1473	3000	2250
	Spoof	1480	3000	2250
Materials		1	3	3
Co-operative		Yes	Yes	Yes

TABLE II
CHARACTERISTICS OF THE DATASETS USED IN LIVDET2011

DATASET		LivDet2011			
		Biometrika	Dig.Pers.	Italdata	Sagem
Model No.		FX2000	400B	ET10	MSO30
Res.(dpi)		500	500	500	500
Image size		312×372	355×391	640×480	352×384
Training Samples	Live	1000	1004	1000	1008
	Spoof	1000	1000	1000	1008
Testing Samples	Live	1000	1000	1000	1000
	Spoof	1000	1000	1000	1036
Materials		5	5	5	5
Co-operative		Yes	Yes	Yes	Yes

TABLE III
CHARACTERISTICS OF THE DATASETS USED IN LIVDET2011

DATASET		LivDet2011			
		Biometrika	Dig.Pers.	Italdata	Sagem
Model No.		FX2000	400B	ET10	MSO30
Res.(dpi)		500	500	500	500
Image size		312×372	355×391	640×480	352×384
Training Samples	Live	1000	1004	1000	1008
	Spoof	1000	1000	1000	1008
Testing Samples	Live	1000	1000	1000	1000
	Spoof	1000	1000	1000	1036
Materials		5	5	5	5
Co-operative		Yes	Yes	Yes	Yes

TABLE 4
PERFORMANCE COMPARISON IN TERMS OF AVERAGE CLASSIFICATION ERROR (ACE) ON LIVDET2009DB

Methods	Average Classification Error (ACE) (%)			
	Biometrika	Crossmatch	Identix	Average
Features based on M_1	14.7	6.2	3.2	8.03
Features based on M_2	8.4	6.42	2.51	5.58
IQA-based [1]	12.8	10.7	1.2	8.2
Perspiration-based feature [2]	12.6	15.2	9.7	12.5
Wavelet feature [3]reported in [2]	23.0	23.5	38.2	28.2
Ridgelet feature [9, 10]reported in [2]	28.3	18.7	30.3	25.8
Ridge frequency feature [14] reported in [2]	28.3	31.5	47.2	36.8
Best result in LivDet 2009 [16]	18.2	9.4	2.8	10.1

TABLE 5
PERFORMANCE COMPARISON IN TERMS OF AVERAGE CLASSIFICATION ERROR (ACE) ON LIVDET2011DB

Methods	Average Classification Error (ACE) (%)				
	Biometrika	Dig.Pers.	Italdata	Sagem	Average
Features based on M_1	8.9	4.75	14.57	6.8	9.0
Features based on M_2	6.93	3.42	12.45	3.69	6.62
MSLBP1 [19]	7.3	2.5	14.8	5.3	7.475
MSLBP2 [19]	10.6	6.7	12.6	5.6	8.875
LPQ [22]	14.7	12	14.4	8	12.3
WLD [24]	13.25	13.75	27.67	6.66	15.333
MLBP reported in [19]	10.8	7.1	16.6	6.4	10.225
Original LBP reported in [19]	13.0	10.8	24.1	11.5	14.85
Best result in LivDet 2011 [27]	20.0	36.1	21.8	13.8	22.925

TABLE 6
PERFORMANCE COMPARISON IN TERMS OF AVERAGE CLASSIFICATION ERROR (ACE) ON LIVDET2013DB

Methods	Average Classification Error (*ACE*) (%)			
	Biometrika	Italdata	Swipe	Average
Features based on M_1	13.2	15.7	10.23	13.04
Features based on M_2	2.35	3.57	4.38	3.43
HIG [30]	3.9	1.7	14.44	6.68
Aug LBP [31]	1.7	2.3	3.3	2.43
Aug CN [31]	0.8	2.5	7.7	3.67
Best result in LivDet 2013[34]	1.7	0.8	3.5	2

$$M_2(s,t,u,v) = \sum_{i=1}^{m-1}\sum_{j=1}^{n-2}\gamma(G_M(i,j),s)\times\gamma(G_O(i,j),t) \times\gamma(G_M(i,j+1),u)\times\gamma(G_O(i,j+1),v), \quad (7)$$

where $s,u \in \{0,\ldots,T\}$, $t,v \in \{-\theta,\ldots,0,\ldots\theta\}$, and $\gamma(x,y) = \begin{cases}1, \text{if } x = y\\ 0, \text{if } x \neq y\end{cases}$. In order to eliminate the influence caused by the image size, the elements of the co-occurrence matrix are normalized as:

$$M_1(s,t) \leftarrow \frac{M_1(s,t)}{\sum_{s=0}^{T}\sum_{t=-\theta}^{\theta} M_1(s,t)}, \quad (8)$$

$$M_2(s,t,u,v) \leftarrow \frac{M_2(s,t,u,v)}{\sum_{s=0}^{T}\sum_{t=-\theta}^{\theta}\sum_{u=0}^{T}\sum_{v=-\theta}^{\theta} M_1(s,t,u,v)}. \quad (9)$$

In this paper, the elements of co-occurrence matrix are directly used as features. For M_1, the number of features is $(T+1)\times(2\theta+1)$, and for M_2, the number of features is $(T+1)^2\times(2\theta+1)^2$.

IV. EXPERIMENTS

A. Databases and Evaluation Criterion

The proposed detection methods are tested on three databases which are released in international Fingerprint Liveness Detection Competition, LivDet09[16], LivDet11[27], and LivDet13[34]. All of the fingerprint images are transformed into gray images before being used. Each of the datasets is divided into two non-overlapping parts: the training and testing sets, which can be used respectively in the training and testing processes of the classification. The general information of the databases is presented in Table 1, 2, and 3. For the three databases, the images captured by each sensor are separately tested.

In the experiment, the average classification error (ACE) of the trained classifier is defined as the evaluation criterion:

$$ACE = (FAR + FRR)/2 \tag{10}$$

where FAR (False Accept Rate) is the proportion of spoof fingerprints being incorrectly accepted, and FRR (False Reject Rate) is the proportion of real fingerprints being incorrectly rejected.

B. Parameter setting

Generally, we would like to quantize the gradient magnitude and orientation with small quantization steps, i.e., small Q and $\frac{\pi}{2\theta}$, so as to get fine-grained values. Also, we would like to choose big truncation parameter T to cover the majority of quantized magnitude values. However, these also cause larger dimensionality of the feature vector. According to our algorithm, the dimensions of feature vectors are equal to $(T+1)\times(2\theta+1)$ and $(T+1)^2\times(2\theta+1)^2$ for M_1 and M_2, respectively. For M_1, we set $T=20$, $Q=1$, and $\theta=10$. In this case both the gradient magnitude and orientation are quantized to fine-grained values, and 95.73% gradient magnitude values, which are calculated from LivDet2011 database, are covered in the range $[0,\ldots,T=20]$. Accordingly, the dimensionality of feature vector based on M_1 equals to 441. For M_2, the feature number is quatratically increased to the parameters T and θ. In order to limit the feature amount, we need to set smaller T and θ, and accordingly, set a relatively big Q to get the majority of magnitudes covered. Specifically, we select $T=4$, $Q=16$, and $\theta=4$ in our experiment. In this case, 95.48% gradient magnitude values are covered, and the dimensionality of feature vector is 2025.

C. Detection results

We compare our work with some state-of-art FSD methods. In addition, the best results achieved in LivDet 2009, LivDet 2011, and LivDet 2013 are also cited for the performance comparison. The detection errors of different methods for three datasets are presented in Table 4, 5, and 6. The results show that the features based on M_2 achieve better detection accuracy than that based on M_1 and many other existing FSD methods.

V. Conclusion

In this paper, we presented a novel fingerprint spoof detection method by using co-occurrence statistics of gradient magnitude and orientation. Firstly, the co-occurrence of magnitude and orientation of one pixel are calculated. In this case, both the magnitude and orientation are quantized with small quantization steps so as to get fine-grained features. Secondly, the co-occurrence of magnitude and orientation of two adjacent pixels are calculated. In this case, we set a relatively big quantization steps for gradient magnitude and orientation so as to limit the dimensionality of the feature vector. The experimental results have shown that the co-occurrence matrix based on two adjacent pixels achieves better detection accuracy. In future, the proposed method can be further improved by considering the co-occurrence of more pixels. The key problem is to limit the dimension of the feature vector.

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