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Fingerprint Liveness Detection Using Difference Co-occurrence Matrix Based Texture Features

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Abstract

Fingerprint authentication systems have been widely deployed in both civilian and government applications, however, whether fingerprint authentication systems is security or not has been an important issue under fraudulent attempts through artificial spoof fingerprints. In this paper, inspired by popular feature descriptors such as gray level co-occurrence matrix (GLCM) and Gradient (difference matrix (DM)), we propose a novel software-based fingerprint liveness detection algorithm called difference co-occurrence matrix (DCM). In doing so, quantization operation is firstly conducted on the images. DMs are constructed by calculating difference matrices of horizontal and vertical pixel values of images; difference co-occurrence arrays are constructed from the difference matrices between adjacent pixels. To reduce the influence of abnormal pixel values, truncation is used for DMs. Then, we compute four parameters (Angular Second Moment, Entropy, Inverse Differential Moment and Correlation) used as feature vectors of fingerprint images. For the first time in the fingerprint liveness detection, we construct eight difference co-occurrence matrices and extract texture features from processed DCMs. Finally, SVM classifier is used to predict classification accuracy. The experimental results reveal that our proposed method can achieve more accurate classification compared with the best algorithms of 2013 Fingerprint Liveness Detection Competition, while being able to recognize spoofed fingerprints with a better degree of accuracy.

Keywords*: Fingerprint liveness detection, difference co-occurrence Matrix, gray level co-occurrence matrix, gradient difference matrix*

1. Introduction

With the increasing advances in technology, the security of identity authentication has become an important issue than ever before. Biometric recognition systems are considered to be more reliable than traditional tokens and passwords, so increasingly more biometric authentication systems have been deployed in all aspects of our daily life. Among these, the fingerprint recognition, the ease of use and high correct rate are the main factors that contributes to their widespread use, accounts for the vast majority part [1]. Spoof fingerprints, which can be easily spoofed from common materials, such as

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silicon, wood glue and latex, are to gain access of a person that is already enrolled. Therefore, how to detect whether a fingerprint belongs to a real fingerprint or spoof artifact has become a huge challenge.

Certainly, these issues have been handled through designing a series of anti-spoofing mechanism based on fingerprint vitality detection methods. The ability of a fingerprint authentication system to discriminate whether the fingerprint samples presented is really from a live finger tip or spoofed ones, which is called the liveness detection. In traditional detection methods, the fingerprint authentication system is coupled with specific hardware and software modules to certify the particular properties of the submitted fingerprints. The hardware-based solution can detect the fingertip of the fingerprint images through exploiting characteristics of liveness, such as pulse oximetry, temperature of finger, electrical conductive of skin and so on, but this type of technique requires the introduction of additional sensor devices which are extremely expensive[2]to detect the traits of fingerprint images. Therefore, in order to reduce cost as well as improve the security, the software-based methods which are cheaper and non-invasive were brought up. In software-based method, we can finish fingerprint liveness detection using only an image by using characteristics of multiple frames of the same fingerprint image.

Therefore, to judge whether a fingerprint is real fingerprint or spoof artifact, various fingerprint vitality algorithms have been proposed. Among these methods, there are two categories of fingerprint vitality detection methods: hardware-based methods applied at acquisition stage, and software-based methods applied at processing stage[3]. The hardware-based methods usually need to add extra sensor devices to detect the particular characteristics of fingerprint image, such as fingerprint sweat, electric resistance and pulse. However, improper integration of additional sensors can lead to higher error rates of liveness detection approaches. In contrast, the software-based methods which use image processing algorithm to gather information directly from the collected fingerprint to detect liveness [4] are cheaper and more convenient solution.

The current fingerprint liveness detection research is concerned about how to design a better feature extraction algorithm. In this paper, we propose a novel fingerprint liveness detection algorithm based on difference co-occurrence matrix from only one image. On the whole, we consider fingerprint liveness detection as two-class classification problem, in which a given fingerprint image is divided into real image or a spoof one. Feature extraction is an important step during the process of classification. Quantization operation is used to reduce the influence of abnormal pixel values. Specifically, two difference co-occurrence matrices are obtained through calculating difference matrices of horizontal and vertical pixel values of images, and truncation operation is used to reduce the influence of abnormal pixel values of a given image. After these, difference co-occurrence matrices are constructed from each difference matrix between adjacent pixels. Then, four different parameters calculating from the processed difference co-occurrence matrices to are used as texture features of the fingerprint images. This paper for the first time designs and applies quantization and truncation operations on the images, which are used to reduce the dimensionality of texture feature vector without reducing the classification accuracy.

The rest of the paper is organized as follows. In Section II a summary of the most relevant concepts to the present study is given. Our proposed method about the feature vector extraction is introduced in Section III. The result and comparison are given in Section IV. Conclusions are finally drawn in Section V.

2. Related Work

Previous works have shown that the software-base fingerprint liveness detection methods can discriminate the real and spoof artifact through analyzing the features extracted from fingerprint images, such as sweat pores, perspiration, image quality, skin elasticity, image texture, these properties can be considered as image features. To illustrate these features, in the present work we categorize the software-based methods into five categories: Perspiration-based, Skin Deformation-based, Image Quality-based, Pore-based and Texture Feature-based.

Perspiration-based methods: Because sweat glands can produce moisture, the obtained live fingerprint images from fingerprint sensors will change slightly in a short time span. However, the obtained spoof fingerprints from fingerprint sensors do not generate moisture. Therefore, we can detect the fingerprint vitality through analysis of image sweat. Derakhshai *et al.* [5] proposed a detection method by acquiring and analyzing perspiration pattern change at different time interval (such as 2 seconds and 5 seconds in [5]). Gray-level values along the ridges are calculated via mapping the two-dimensional fingerprint images into one-dimensional signal. In their method, they can find that the longer the time interval, the more complex wavy nature based on the spreading of moisture in the live fingerprint. In contrast, no similar phenomenon occurred in spoof fingerprints no matter how long the time interval is. In order to solve the problem and improve the accuracy of Derakhshai *et al.* proposed method. Abhyankar *et al.* [6] proposed a novel liveness detection method which can isolate the perspiration pattern by using wavelet analysis. In their method, multi resolution analysis extracts the low frequency content and wavelet packet analysis extract the high frequency content. Then, the feature was extracted by using energy content of changing coefficients intensity. After that, Tan and Schuckers [7] also proposed a method to detect the fingerprint liveness which is based on quantity perspiration. This method quantifies the level of fingerprint through analyzing histogram of data distribution. Besides that, they also do some research on the perfect performance, such as reducing the capture time and increasing the feature dataset.

Skin Deformation-based methods: It is true that live fingerprint can generate high distortion compared with spoof ones when fingers press and rotate on the fingerprint sensor. Therefore, the obtained content based on the deformation can be considered as the feature of fingerprint image. Zhang *et al.* [8] proposed a liveness detection method based on thin-plate model. In their method, the testers were asked to rotate their fingers in four different angels to acquire a sequence of different fingerprint. Then, the features are extracted based on the skin deformation-based from capturing finger distortion images. Jia *et al.* proposed a liveness detection method using one-way analysis of variance - ANOVA and Multiple Comparison Method to do the statistical tests on the dataset of real and fake fingers [9]. In their method, the tester needs to put his fingers on the scanner devices, and then a sequence of fingerprint images is captured. The features are extracted from the sequence of images. No extra hardware or special finger movement is required in this method.

Image Quality-based methods: Generally, because artificial spoofed fingerprint material can agglomerate during the processing, the surface of spoofed fingerprints is coarser than real fingerprints. Because fake fingerprint image quality is not as good as the real fingerprint image, it is difficult to forge a real fingerprint image with the same or better quality fingerprint images. Nikam and Agarwal [10]checked the liveness of fingerprint based on ridgelet transform to extract image texture features using only one fingerprint image. In their method, through the study of uniformity of gray levels along the ridges, they observed that the textural features of a live fingerprint image are simpler than an artificial spoofed one. Tan *et al.* [11] proposed a fingerprint vitality detection method based on wavelet analysis. In their method, they observed that spoofed fingerprint has some different noise along the fingerprint valley, while the ridge-valley structure of live fingerprint along the fingerprint valley is clean. The quality features are extracted via using this approach. In 2013, Pereira *et al.* [12] detected the vitality of fingerprint images based on residual Gaussian white noise of the fingerprint images to estimate the coarseness of fingerprint image.

Sweat Pore-based methods: The researchers observed that it is difficult to accurately imitate sweat pores in a spoofed fingerprint, since the pores are some very small circular structures. Espinoza *et al.* [13] detected the liveness of fingerprint image based on comparing different query fingerprints and the recorded ones pore quantity. Pores are considered as the fingerprint liveness signal. Manivanan *et al.* [12] proposed a new method to detect fingerprint liveness based on pores as a sign of fingerprint. Their paper applies two filtering techniques: highpass filter which was used to extract active sweat pore and correlation filter which was used to locate the position of pores. After that, in 2010, Manivanan *et al.* [14] proposed a vitality detection method based on detecting pores. In their method, only one fingerprint image is needed, and two filtering techniques were used, such as correlation and high pass. The former filter is used to locate the position and sweat pores, and the latter is used to extract the texture feature of fingerprint image.

Texture Feature-based methods: Texture used for indentifying regions of interest (ROIs) is an important feature in a fingerprint image. Many methods have been developed for analyzing texture, such as statistical, structural, model-based and signal processing approaches [15]. From these methods, the most fundamental method for extracted fingerprint image textural features is statistical analysis, which can calculate the textural feature. Abhyankar *et al.* [20] developed a fingerprint vitality detection method based on minimize the energy associated with phase and orientation maps. In their method, multi-resolution textural feature analysis and cross ridge frequency analysis techniques are applied. The features including the first order features, such as median, entropy, energy, and variance of the histogram, and the second order features, such as cluster shade and cluster prominence of the gray co-occurrence matrix are extracted [20]. Jhat *et al.* [21] extracted texture features by an algorithm based on the spatial gray level dependence method, which proposed using the statistical texture analysis of a fingerprint by using spatial gray level dependence method (SGLDM) for personal verification and discrimination. Nikam *et al.* proposed many fingerprint liveness detection method based on texture features extraction, such as the curvelet transform [16]. In 2014, Diego Gargnaniello *et al.* [17] proposed a liveness detection based on spatial domain and transform domain. In their method, to extract information on the local behavior of the image, and on the local amplitude contrast, they needed to analyze the input fingerprint image both in the spatial domain and the frequency domain.

3. Feature Extraction

The extraction of image features is the foundation of the research on liveness detection. Generally, the fingerprint image liveness detection is divided into a two-class classification problem, detecting a given fingerprint images to be either real fingerprints or spoofed ones. The flowchart showing different phases of our approach is shown in Figure 1, which mainly including two phases: image training process phase and image testing process phase. Based on two methods of difference matrix and gray level co-occurrence matrix, we propose a novel method based on difference co-occurrence matrix (DCM). In our method, DM is constructed by calculating difference matrices of horizontal and vertical pixel values of images; difference co-occurrence arrays are constructed from the difference matrices between adjacent pixels. The key point of the vitality detection is to construct an appropriate feature vectors. In our proposed approach, the process of feature extraction operation is as follows. Firstly, quantization operation is applied to reduce the grayscale and the dimension of features. Secondly, the differences of adjacent horizontal and vertical pixel values generate a new matrix (We can work out two difference co-occurrence matrices in the horizontal direction and in the vertical direction). Moreover, truncation operation is used to reduce the gray range of gray level. After these, difference co-occurrence matrices are constructed from each difference matrix between adjacent pixels. Then, four parameter values (Angular Second Moment, Entropy, Inverse Differential Moment and Correlation) are computed from each DCM which are regarded as the textural features of fingerprint image, and the texture feature vectors are obtained by using the DCM. Finally, SVM classifier is used to predict classification accuracy.

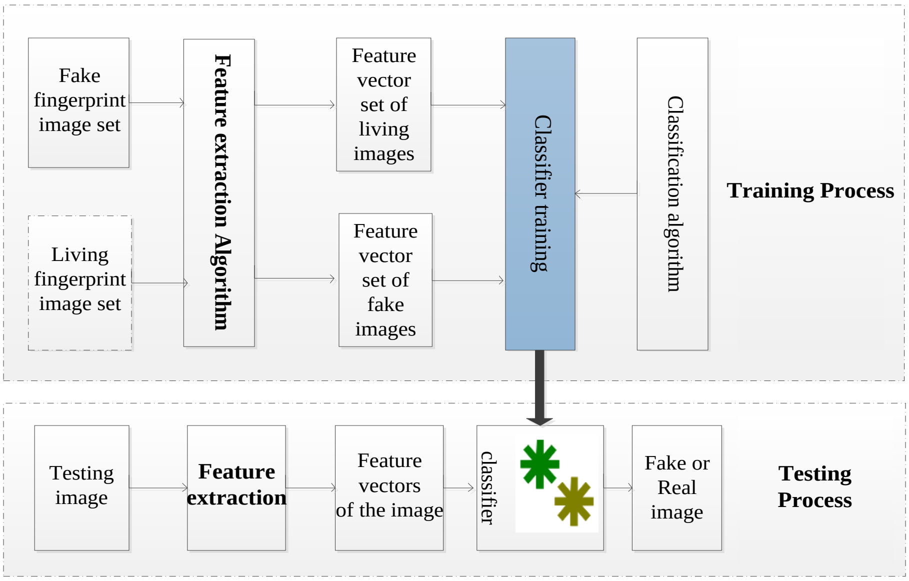


Figure 1. The Flowchart Showing Different Phases of Our Approach

Compared with the state-of-the-arts, our proposed approach can reduce the use of memory space, since the dimensionality of extracted features is small. Moreover, it is cheap and convenient to embed in hardware, while the experimental results present that our approach can achieve a good result. Next we will detailedly describe our method about feature extraction of image.

3.1. Quantization

In general, the gray values of neighbored pixels of image are equal or similar, so many zeros elements would be generated in the DCM without processing the original image. Meanwhile, it also increases the dimensionality of feature and the computational complexity. Therefore, in order to extract a useful feature vectors, quantization operation is used. In this paper, 8 bits gray image can be expressed as G, the G is calculated as: $G=(G_{i,j}) \in \{0,\ldots,255\}^{n_1 \times n_2}$. In the symbol, the height and width of given images are denoted as n_1 and n_2, respectively. $G_{i,j}$ denotes the pixel values which is located at (i , j). Therefore, we can solve above problem about the image grayscale by using quantization operation technology. The quantization operation not only decreases the computational cost through reducing the range of $G_{i,j}$, but also reduces the grayscale of images. Pixel values of images are quantized as:

$$G_{i,j} \leftarrow \lfloor G_{i,j} / Q \rfloor \quad , \tag{1}$$

In equation (1), the symbol $G_{i,j}$ denotes the grayscale value of the pixel which is located at (i , j), Q is the quantization factor, where Q is an integer greater than or equal to 1. Quantization operation can reduce the quality of the images, but the influence of texture features almost is not considered. The bigger the quantization factor is, the smaller of the value of difference is.

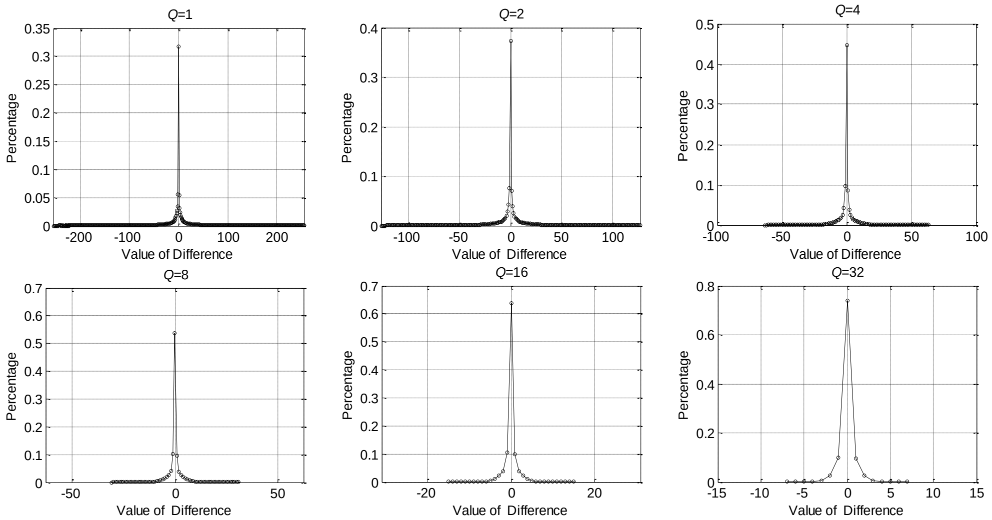


Figure 2. The Histograms of Vertical Difference Calculated fom Quantized Fingerprint Images, Q = 1, 2, 4, 8, 16, 32

3.2. Pixel values Difference and Truncation

Pixel values difference is calculated between two adjacent pixel values, which can measure a gray change in fingerprint images. In our method, we can construct two difference co-occurrence matrices through computing the difference of joint two horizontal or vertical of pixel gray values on the images. We define the difference arrays in horizontal direction and in the vertical direction as D_{H} and D_{V} respectively. The calculations of D_{H} and D_{V} are given bellow:

$$\begin{cases} D_H(i,j)=G_{i,j}-G_{i,j+1} \\ \qquad\qquad for\ i\in\{0,\ldots,n_1-1\}, i\in\{0,\ldots,n_2-2\}; \\ D_V(i,j)=G_{i,j}-G_{i+1,j} \\ \qquad\qquad for\ i\in\{0,\ldots,n_1-2\}, i\in\{0,\ldots,n_2-1\}; \end{cases} \tag{2}$$

The calculation cost of textural feature depends on the dimensions of difference co-occurrence matrix. Figure 2 shows that *we* can reduce the wave range of the value of vertical difference through setting a larger quantization factor Q. The larger the quantization factor Q, the smaller the range of value of difference. In our method, we set the quantization factor Q as 1. Additionally, in order to deal with abnormal values, the truncation operation is proposed in our method. We can use truncation operation technology to truncate the values of difference to a probable range [-T, T] without losing much using features, meanwhile, reducing the influence of outliers, where T is the given threshold. The formula for truncation operation is following:

$$D(i,j) \leftarrow TC(D(i,j)), \tag{3}$$

where $D(i,j)$ denotes the difference arrays in horizontal direction and vertical direction located at (i, j). TC( ) denotes truncation operation. The rules are defined as:

$$\begin{cases} TC(D(i,j))=T & D(i,j)>T \\ TC(D(i,j))=-T & D(i,j)<T \\ TC(D(i,j))=D(i,j) & D(i,j)\in[-T,T] \end{cases} \tag{4}$$

where T is set as a constant, and T is greater than or equal to 1. Besides these, normalization is also necessary, since features results can be controlled in the specified range. After these, we can calculate four parameters (Angular Second Moment, Entropy, Inverse Differential Moment and Correlation) which are used as textural feature by using processed DCM.

3.3. Difference Co-occurrence Matrix

Difference co-occurrence matrix includes two processes: Difference matrix and Gray level co-occurrence matrix. Difference matrix can be constructed by calculating the difference of gray value of adjacent two rows or two columns pixel in an image. DCM can not only present the distribution characteristics of brightness, but also reflect the change of gray values. We can obtain two difference matrices in the horizontal direction and in the vertical direction using Eq.2. Next, we will give a detailed introduction about the DM. Figure 3 describes an example of the calculation of DM. Such as the first and second columns of the first row in Figure 3 (a), which are shown in black circle, the difference value of the first and second columns of the first row using the Eq.2 is 1, and then the values will be considered as one element of obtained matrix. For example, the difference value is presented using black circle in the first column of the first row in Figure 3 (b). Similarly, the difference value of the third and fourth columns of the third row and the difference value of the fourth and fifth columns of the forth row value which are shown as in Figure 3(b) are 3 and 3 using the Eq.2, respectively. Finally, we can get a difference matrix Figure 3(b). Gray level co-occurrence is a matrix of pixel values, which is constructed by computing the number of the occurrence between adjacent pixels. We can denote the GLCM using symbol $P(i,j,d,\theta)$. $P(i,j,d,\theta)$ is said that the number of the pair of gray values of i and j appears in the original gray image besides that d denotes the distance between two pixel values and θ denotes the angle of pixel values. In our method, we set the value of distance d as 1 and θ as 0° ,45° , 90° and 135° respectively. Figure 3(c) shows an example of the calculation of GLCM, The first row and first column denotes the gray level of original image. In the case of $(1,1)$ in Figure 3(b), the value of $P(1,1,1,0^{\circ})$ is 3 in Figure 3(c). In other word, the frequency of occurrences of adjacent pair of gray value 1 and 1 when the distance of adjacent pixel is 1 and the direction of adjacent pixel is 0° is 3 in Figure 3(b). Similarly, the value of $P(1,2,1,0^{\circ})$ is 2. While the θ changes from 0° to 45° , 90° and 135° respectively, we can get gray level co-occurrence matrices of three different directions. Finally, Figure 3(c) is the final DCM of the given gray image matrix.

6	7	8	9	12
3	4	9	10	12
4	7	9	12	16
1	6	7	8	12
7	8	10	11	14

(a)

1	1	1	3
1	5	1	2
3	2	3	4
5	1	1	4
1	2	1	3

(b)

f1/f2	1	2	3	4	5
1	3	2	2	1	1
2	1	0	1	0	0
3	0	1	0	1	0
4	0	0	0	0	0
5	2	0	0	0	0

(c)

Figure 3. Fingerprint Image Matrix: (a) Grayscale Value Matrix of the Part of Fingerprint Image, (b) Difference Matrix in the Horizontal Direction, (c) Gray Level Co-occurrence Matrix when Distance d is 1 and Angle θ is 0°

According to the above method, we compute eight DCMs by using Eq.2 and GLCM. In our approach, we only select and compute four typical and universal parameters as the image textural feature compared with [17] by DCM. Therefore, based on DCM, four textural feature values (Entropy, Angular Second Moment, Correlation and Inverse Differential Moment) are used as the texture feature of each DCM. These feature values are calculated as the following Eqs.(5)-(8):

$$ASM = \sum_{i=1}^{k}\sum_{j=1}^{k}(P(i,j))^2 , \tag{5}$$

$$E = -\sum_{i=1}^{k}\sum_{j=1}^{k}P(i,j)logP(i,j) , \tag{6}$$

$$I = \sum_{i=1}^{k}\sum_{j=1}^{k}\frac{P(i,j)}{1+(i-j)^2} , \tag{7}$$

$$C = \sum_{i=1}^{k}\sum_{j=1}^{k}\frac{(i\cdot j)P(i,j)-u_i u_j}{s_i s_j} , \tag{8}$$

where in equation (8),

$$u_i = \sum_{i=1}^{k}\sum_{j=1}^{k} i\cdot P(i,j) , \qquad u_j = \sum_{i=1}^{k}\sum_{j=1}^{k} j\cdot P(i,j) ,$$

$$s_i^2 = \sum_{i=1}^{k}\sum_{j=1}^{k}P(i,j)(i-u_i)^2 , \qquad s_j^2 = \sum_{i=1}^{k}\sum_{j=1}^{k}P(i,j)(j-u_j)^2 .$$

4. Experiment

In this section, the performance of our classification algorithm is verified by using three official datasets: LivDet 2009 [2], LivDet 2011 [4] and LivDet 2013 [19], which are the publicly available datasets provided in the Fingerprint Liveness Detection Competition. Firstly, we give a brief introduction about the three databases. Secondly, feature vectors classification is introduced using SVM classifier. Then, the validation criterion is applied which is used to describe the performance of our method. Finally, we also conduct experiments based on the Fingerprint Liveness Detection Competition LivDet2009, LivDet2011 and LivDet2013 databases, besides we compare our proposed method with the state-of-the art works.

4.1. Databases

Since 2009, to assess the performance of the proposed state-of-the-art fingerprint liveness detection methods, the Department of Electrical and Computer Engineering of the Clarkson University (USA) and the Department of Electronic Engineering of the University of Cagliari(Italy) have held a LivDet Competition[2] [4] [19]. In our method, experiments are conducted by using the datasets which are provided by the LivDet (Liveness Detection Competition)of 2009 [2], 2011 [4] and 2013 [19]. And all the LivDet sets were divided into two parts: training set, which is used to fine tune the approach, and a testing set, used to estimate the performance of results.

LivDet 2009 fingerprint images are composed of three different flat optical sensors (a. Biometrika FX2000 (569 dpi), b. CrossMatch Verifier 300LC (500 dpi), and c. Indentix DFR2100 (686 dpi)), including 7723 real fingerprints and 7730 spoof fingerprints which were captured by using three different materials, such as Play Doh, Silicone, and Gelatin. Some of them are trained and the rest of them are tested via using the SVM.

LivDet 2011 fingerprint images are composed of four different optical sensors (Biometrika FX2000 (500 dpi), Digital 4000B (500 dpi), Italdata ET10 (500 dpi), and Sagem MSO300 (500 dpi)). Half of datasets are trained and the others are tested using the SVM. Spoof fingerprints were captured by using four different materials, such as Sagem, ItlData, Biometrika and Digital Person.

LivDet 2013 fingerprint images comprise four different flat optical sensors (a. Italdata ET10(500 dpi), b. CrossMatch Verifier 300LC (500 dpi), c. Biometrika FX2000 (569 dpi) and d. Swipe(96 dpi)), including 8775 real fingerprints and 8981 spoof fingerprints which were captured via using five different materials, such as Gelatin, Ecoflex, Latex, Modasil, and WoodGlue. Half of them are trained and the rest of fingerprints are tested using the SVM.

Table 1. Table of the Detailed Information of Livdet2009, Livdet2011 and Livdet2013

DATASET	LiDet2009			LiDet2011				LiDet2013			
Scanner	Biometrika	Cmatch	Identix	Biometrika	Dig.Pers	Italata	Sagem	Biometrika	Cmatch	Italata	Swipe
Model No.	FX2000	V300LC	DFR2100	FX2000	400B	ET10	MSO300	FX200	V300LC	ET10	---
Res.(dpi)	569	500	686	500	500	500	500	569	500	500	96
Image Size	312x372	480x680	720x720	315x372	355x391	640x480	352x384	352x384	800x750	480x640	1500x208
Live Sample	1473	3000	2250	1000	1000	1000	1000	1001	1250	1000	1221
Fake Sample	1480	3000	2250	1000	1000	1000	1036	1000	1000	2005	976

Each dataset is divided into a test set which is used to evaluate results and a train set which is used to build up model. More information is reported in Table 1on the LivDet. In Table 1, we illustrate the detailed information of the fingerprint. From the Table 1, we can clearly observe the difference of different LivDets. Some typical sample images of real and spoof fingerprints are presented in Figure 4. It is difficult for us to observe the differences of different fingerprints just with our eyes. And the ranges of fingerprint image size from 240×320 to 700×800 pixels.

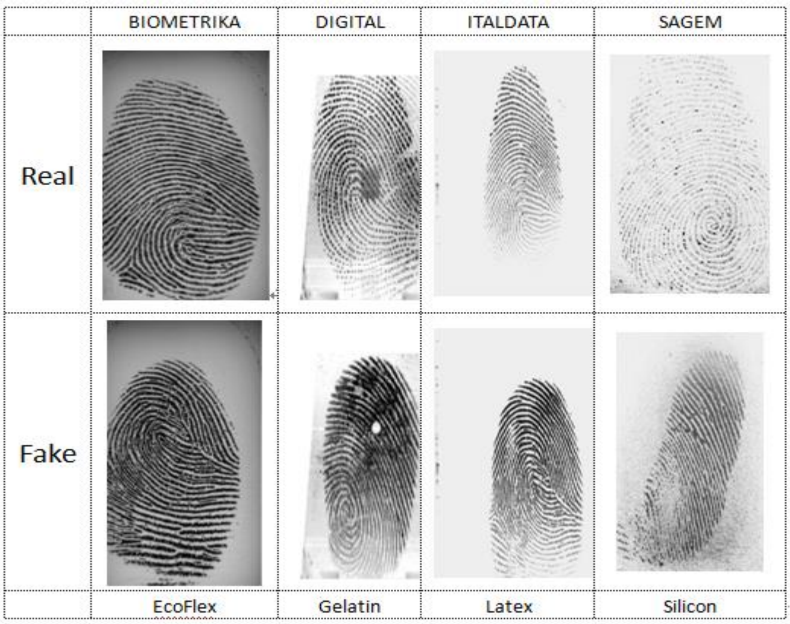


Figure 4. Typical Sample Images of Real and Spoof Fingerprints those can be Found in the Livdet 2011

4.2. Classification

SVM (a kind of machine learning algorithm) is a useful technology for solving feature data classification problems. In this paper, a SVM with a Gaussian Radial Basis Function (RBF) kernel is used as classifier since it has shown slightly better performance than others' kernels. LIBSVM software package [18] which is a research of classification algorithm is the most commonly used tools. When we use SVM, two key issues need to be considered.

One problem is related to the selection of kernel function. According to the linear separable and linear inseparable, we can use different kernel functions. To make the samples classification easier and more accurate, the radial basis function (RBF) kernel makes nonlinearly mapping to a high-dimensional space. It notes that the class labels and features are all nonlinear. In our method, because of the advantages of a less complex model and less parameters, RBF kernel function is selected.

Another problem is about how to select appropriate kernel parameters. There are two parameters in the RBF kernel function: C and Υ. To find the best testing and training classification parameters, parameter optimization method is used. The executable file of parameter optimization method in LIBSVM is gnuplot.exe. We can find the best pairs of classification parameter C and Υ by using the executable file, while the goal of the parameter optimization method is to obtain pairs of classification parameter and classify the unknown data. Through the tool “Grid-search and Cross-validation”, we can search the results of the optimal.

4.3. Performance Metrics and Results

The LivDet 2011DB derives from 2011 Fingerprint Liveness Detection Competition, where the quality of the spoof fingerprints has greatly improved, and they are distributed through the website of the competition. We have discussed the detailed information of the LivDet 2011DB in Part A. The performance of our method is validated based on the Average Classification Error (ACE) methods, which is considered as standard metric for validation the different LivDets. In our experiment, ACE is considered as the validation criterion, which is defined as:

$$ACE = (FAR + FRR) / 2\ , \tag{9}$$

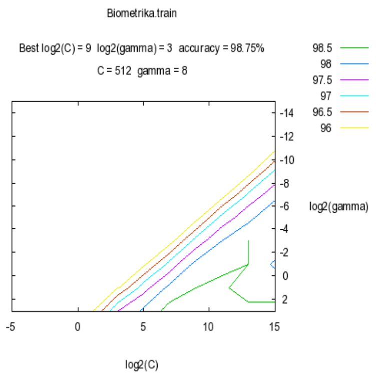
where in equation (9),

$$FAR = \frac{Total\ Number\ Imposter\ Fingerprints\ Accepted\ as\ Genuine}{Total\ Number\ of\ Forgery\ Tests\ Performed}\ , \tag{10}$$

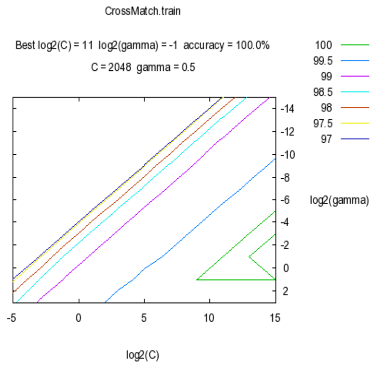
$$FRR = \frac{Total\ Number\ Genuine\ Fingerprints\ Accepted\ as\ Imposter}{Total\ Number\ of\ Genuine\ Matching\ Tests\ Performed}\ , \tag{11}$$

In the equation (9), where the False Accept Rate represents the percentage of fake fingerprints being incorrectly accepted and the False Reject Rate (FRR) computes the percentage of real fingerprints being considered as fake class. In our method, two successive processes are designed to obtain the best classification accuracy in the process of the experiment, including training and testing processes:

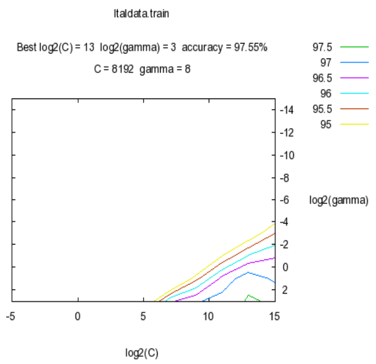
Process 1: Training process. Aiming at finding the optimal textural features datasets, we propose a new method based on difference co-occurrence matrix. Using each processed DCMs, we can compute four parameters which are designed as the textural feature of fingerprint image. Therefore, feature vector of each image is composed of 32 parameters which are calculated by eight DCMs. After that, executable file svm-train.exe is used to train the obtained feature vectors in SVM classifier. In order to make the results more persuasive, parameters optimization is a crucial step for training process. Figure 5 shows that results of parameters optimization based on different sensors. For example, the same color describes the same accuracy. In Figure 5(a), the green lines present the highest classification accuracy when the value of parameter pair (C, Υ) is (512, 8). And the classification accuracy is 98.75%. That is to say, we can obtain the best classification accuracy when we set parameter pair value in the next of testing process. Similarity, the best accuracy responding the Figure 5(b), (c), (d) can be found. If not, we require to try use different parameter pair (C, Υ) to gain the best classification accuracy.



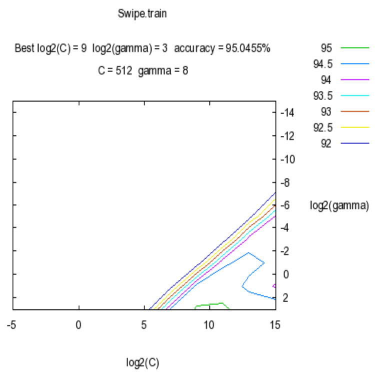
(a) Results of the Biometrika Sensor



(b) Results of the CrossMatch Sensor



(c) Results of the ItalData sensor



(d) Results of the Swipe sensor

Figure 5. Results of the Parameter Optimization Based on different Sensors in LivDet2013

Process 2: Testing process. In our method, the features of image are extracted from the Difference Co-occurrence Matrix. The detailed solution about DCM is described in part Ⅲ. Before calculating the DCM of the given fingerprint images, we need judge whether the images are gray images or not. If not, we need to change the given RGB images into gray images. In our experiment, given quantization factor Q is 1 and the truncation factor T is set 5, and the detailed operations are according to the Eqs.(2)-(4). The Testing and Training processes are measured on MATLAB R2010a. We can obtain four common properties from each DCM, such as Entropy, Angular Second Moment, Correlation and Inverse Differential Moment as the textural feature. As mentioned before, we use the executable file svm-train.exe tool to select the best parameter pair (C, Υ) as the parameter pair of validation of classification. The ACE detection accuracy and its comparison with the proposed methods for detecting fingerprint image vitality are shown in Tables 2, 3 and 4. The accuracy of best designed algorithms from LivDet 2013 and the others' proposed method are shown in Table 2. It shows that our method achieve detection accuracy is superior to the best algorithm proposed in the LivDet2013. In order to facilitate the readers to observe, the best obtained values in Table 2, Table 3 and Table 4 are highlighted in bold. We can find that our method achieving average accuracy ACE

(Average Classification Rate) is obviously superior to other ones in LivDet 2013 and LivDet 2011 or similar to the best algorithms in LivDet 2009.

5. Conclusion

Fingerprint authentication systems have been widely deployed in numerous civilian and government applications, and the ease of use and high classification rates are the main reasons that contribute to their widespread use. However, the attackers can use an artificial fingerprint to gain unauthorized access to the system which is protected by the fingerprint sensors. Therefore, security of fingerprint authentication systems can be threatened by the spoof artifacts. In this paper, inspired by popular feature descriptors such as difference matrix (DM) and the gray level co-occurrence matrix (GLCM), we propose a novel software-based fingerprint liveness detection approach to detect the vitality of fingerprint images. Firstly, quantization operation is necessary, since we can reduce the dimensionality of fingerprint images; another advantage is that many useful textural features are generated. Secondly, DCM is constructed by calculating the difference matrix and gray level co-occurrence matrix of value, Then, in order to reduce the influence of abnormal pixel values, truncation is used for DCMs. Thirdly, we can compute four texture feature parameters of each DCM which are been as texture feature vectors of the fingerprint images using processed DCM. Last but not least, after the obtained trained dataset is trained by the SVM trainer, we can get a SVM model. With the help of the trained model, we can predict the test dataset classifier accurately via using the predict method of libSVM. The performance of our proposed method is assessed on some available datasets which is provided in the Fingerprint Liveness Detection Competition LivDet 2009, LivDet 2011 and LivDet 2013 datasets. The experimental results clearly demonstrate that our method achieves better performance and more effective for fingerprint images quality estimation with respect to the other algorithm under comparison.

The classification rate of datasets is extremely affected by the noise during the classification phase. When we consider the noise of fingerprint image, the tested results are unsatisfactory. Yet, we can lower the influence of different noise through introducing noise filters with idea from Jin et al [20]. Besides, we will also select and calculate different parameter values to detect the vitality of fingerprint image using GLCMs. These will be done in our future works.

Table 2. The Results of the Best Different Algorithms of Livdet 2013 in Terms of Average Accuracy are Cited from [19]

Methods	The Average Classification Error ACE in (%)				
	Bimometrika	Cmatch	Italata	Swipe	Average
Our method	2.55	**44.44**	3.6	10.68	**15.32**
Dermalog[19]	**1.7**	55.47	0.8	**3.53**	15.38
Anonym1[19]	2.0	49.47	1.15	N.A	N.A
ATVS[19]	5.05	54.8	50	46.45	39.08
Anonym2[19]	1.8	54.8	**0.6**	5.81	15.75
UniNap2[19]	6.55	52.13	9.45	26.85	23.75
Anonym3[19]	5.7	53.11	2.8	5.25	16.72
HZ-JLW[19]	32.95	55.56	13.15	15.19	29.21

Table 3. The Comparison in Terms of ACE in Database of the Livdet 2011

Methods	The Average Classification Error ACE in (%)				
	Bimometrika	Digital	Italata	Sagem	Average
Our method	16	8.3	**9.05**	**3.78**	**9.28**
MLBP[16]	**10.8**	**7.1**	16.6	6.4	10.23
Original LBP [16]	13	10.8	24.1	11.5	14.85
Power Spectrum [21]	30.6	27.1	42.8	31.5	33
Dermalog [16]	20	36.1	21.8	13.8	22.93
Federico [16]	40	8.9	40	13.4	25.57
Curvelet GLCM [16]	22.9	18.3	30.7	28	24.98
Walvelet Energy[16]	50.2	14	46.8	22	33.25
Tan's method[16]	43.8	18.2	29.6	24.7	29.08
Curvelet energy [16]	45.2	21.9	47.9	28.5	35.88
Best Result in LivDet2011[4]	20	36.1	21.8	13.8	22.93

Table 4. The Comparison in Terms of ACE in Database of the Livdet 2009

Methods	The Average Classification Error ACE in (%)			
	Bimometrika	Cmatch	Identix	Average
Our method	15.45	**5**	3.3	**7.92**
Moon *et al.*[22]	23	23.5	38.2	28.2
IQA-based [22]	12.8	10.7	**1.2**	8.2
Marasco *et al.* [22]	**12.6**	15.2	9.7	12.5
Best Result in LivDet09 [2]	18.2	9.4	2.8	10.1
Nikam *et al.* [22]	28.3	18.7	30.3	25.8
Abhyankar *et al.* [22]	31.7	31.5	47.2	36.8

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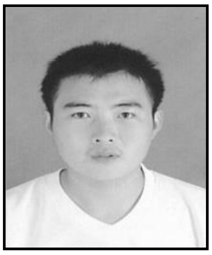

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