# Fingerprint Liveness Detection Adapted to Different Fingerprint Sensors Based on Multiscale Wavelet Transform and Rotation-Invarient Local Binary Pattern

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## Abstract

In recent years, fingerprint authentication systems are convenient for us to verify the identity of the user by extracting and analysing these biometric features, so they have been rapidly developed in our daily life. However, current existing problem is that fingerprint authentication systems are vulnerable to spoofing attacks, such as artificial fake fingerprints. Moreover, the classification accuracy of traditional liveness detection methods for different sensors is not satisfactory. Therefore, in order to solve these spoofing attacks and enhance the classification performance for samples of different fingerprint sensors, a new software-based fingerprint liveness detection method, which is based on the multiscale wavelet transform and the rotaion-invarient local binary pattern (RILBP), was proposed in this paper. The fingerprint samples are derived from four different fingerprint sensors in LivDet 2011. Experimental results demonstrate that our method can detect the fingerprint liveness with higher classification performance compared with other methods of fingerprint liveness detection.

**Keywords:** Fingerprint liveness detection, Fingerprint sensor, Multiscale wavelet transform, Rotation-invarient local binary pattern

## 1 Introduction

With the extensive use of biometric authentication systems, the security of the authentication system has attracted more and more researchers' attention. Owning to biometrics authentication system can analyze and recognize identification based on physiological and behavioral characteristics of objects, therefore, biometric autheication systems have been developed rapidly and deployed in various security applications. The biometric features, such as faces features, fingerprints features and Iris features, are unique for any human being, and the biometric authentication systems are widely used in our daily life. Compared with traditional password methods, biometric methods do not need users to remember some complex passwords. Moreover, it is hard to make a copy of exactly the same biometric features. Therefore, it is more convenient for us to use and popularize in our daily life. Among these, the liveness detection of fingerprint authentication systems has been an active research topic over the last several years [1, 22, 24-25]. Due to the excessive use of fingerprint authentication, the authentication systems have become a target of attacks. For example, the existing problem of fingerprint authentication systems is following: spoof finger can cheat and access the system at the sensor, spoof fingerprint can cheat and access the system on software modules, etc. [5]. Indeed, early fingerprint autentication systems can be easily spoofed and accessed by artificial fake fingerprints, which are reproduced by using popular fake fingertip materials such as silicon, wood glue and latex [3]. Figure 1(a) is a kind of materials of fake fingerprint production, which are candle and silica gel. Figure 1(b) is one of various fingerprint sensors. Different sensors can obtain different fingerprints, and fingerprint authentication systems can be cheated by using artificial fake fingerprints. Therefore, it is necessary for us to design a fingerprint liveness detection algorithm to detect the liveness of different fingerprints, which come from different fingerprint sensors.

Whether a given sample is from a live fingerprint or spoofed one, the ability of discriminating is called liveness detection. In order to prevent the systems being deceived, various kinds of liveness detection methods have been proposed [4-6] in recent years. The texture features, which express either the fine structure or the macros-copic structure, are important characteristics for identifying fingerprint. Currently, the fingerprint detection methods are broadly divided into two groups: the one is the hardware-based

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(a) (b)

**Figure 1.** (a) The materials of making fake fingerprints and (b) fingerprint sensor

approach applied at acquisition stage, and some of them rely on dedicated additional hardware embedded in the sensor, which distinguishes the liveness of given samples by measuring fingerprint properties, such as temperature, blood pressure, pulse, electric resistance and odor, oxiometry, etc. [7]. In the hardware-based method, the fingerprint liveness can be detected by measuring particular traits of fingerprint, and it turns to be more robust to many image attacks and guarantee a higher reliability. Since additional sensors devices are installed, it makes the system structure complex and the cost of implementation high. Another way is that Software-based approach, applied at processing stage [8]. Due to lower cost and without extra sensor devices, software-based methods are more popular in fingerprint liveness detection. Software-based approaches can analyze the fingerprint through analyzing and extracting intrinsic properties directly from given fingerprints.

For fingerprint liveness detection, designing a features extraction algorithm is significant. A better algorithm by analysing the features of natural language was proposed [2]. There are many liveness detection algorithms such as in [8-9], in which the corresponding to fingerprint features based on specific fingerprint measurements, such as ridge strength, continuity and clarity, are extracted. Local descriptors [10-13, 23], as the name suggestion, describe the local statistical characters in very small patches of the image by the means of frequencies of occurrence collected over the ensemble of all patches. These frequencies are used as features to judge the images by the means of conventional classification methods. Based on a local descriptor method usually perform a better result than previous classification methods. In [12], SIFT is used to be extracted the local feature, and the experimental result is satisfactory compared with other method. Before the extraction of texture features, the collection of fingerprints databases is required. In the traditional fingerprint liveness detection methods, whether they are hardware-based or softarew-based, the finerprints are collected through using four different fingerprint sensor in LivDet2011, which are Biometrika sensor, Digital sensor, Italdata sensor and Sagem sensor. It is different for different fingerprint sensors to detect the classification accuracy using these propsoed methods.

## 2 Motivation

The goal of the fingerprint liveness detection research is concerned about how to extract a robust texture feature and meanwhile to make average classification error of fingerprint of four different sensors minimum. Therefore, in order to solve the above problems, designing a feature extraction algorithm is very important for fingerprint liveness detection. In recent years, researchers have proposed many liveness detection methods to detect the liveness of fingerprint. However, the average classification errors corresponding to their methods are not all optimal for different fingerprint sensors. In this paper, a new fingerprint liveness detection algorithm using the multiscale wavelet transform and rotation invarient local binary pattern has been proposed. Multiscale wavelet transform analysis has been proved to be useful for feature extraction, since it can get the same frequency sub-band coefficient together by using a layer wavelet transform. In our paper, the original fingerpirnt is decomposed into four different sub-band coefficients after a layer wavelet transform. After a layer wavelet transform, the fingerprints are transformed from the spatial domain into frequency domain. Original LBP operator is the gray scale invarient, but not the rotation invarient. Fingerprint could be rotated during the communication channel, thus, the extracted features are not the real features of original fingerprint. Finally, the system verification will fail when using fingerprint authentication system. In order to solve the problem and extract more robust textural features, rotation invarient local binary patten has been exploited in our paper. These extracted features are robust through using RILBP. After the above two steps, feature vectors corresponding to four different sub-band coefficients are constructed through using the rotation invariant local binary pattern. The training model is obtained by using the support vector machine classifier. The fingerprints sets are collected through using four different sensors in Livdet 2011. The experimental results have shown that our method can achieve the best performance in the latest literatures.

The system architecture of our method is shown in Figure 2. As we can observe that two main processes are included: the training process and the testing process. Both in training process and testing process, the feature extraction is vital for liveness detection. In addition, the fingerprint image sets are collected by using four different fingerprint sensors, which are Biometrika sensor, Italdata sensor, Sagem sensor and Digital sensor. The fake fingerfrints are generated by using different materials, and then the fake fingerprints using different sensors are collected. After the texture feature vectors are obtained, the SVM classifier is used to estimate the performance of our method. Firstly, lt is necessary for parameter optimization to obtain an optimal training model through using gnuplot.exe in the svm classifier. Next, a training model corresponding to the training sets is gained by using svm-train in the SVM classifier. Finally, with the help of SVM classifier, classification accuracy corresponding to testing fingerprint sets is predicted by using svm-predict. We can detect the liveness of the fingerprint based on the trained model. Experiments have been conducted based on different fingerprint sensors, which are parts of the LivDet 2011 and collected using four different fingerprint sensors.

The paper is organized as follows. In Section 3, a summary of the most relevant concepts to the present study is given. Our proposed method about the feature vector construction and experiment are introduced in Section 4. Conclusions and future works are drawn in Section 5.

## 3 Related Knowledge

In order to prevent the fake fingerprint from accessing successfully fingerprint authentication and meanwhile reduce average classification error for different fingerprint sensors, we propose a new fingerprint liveness dection method by using the multiscale wavelet transform and rotation invarient local binary pattern. In our method, the feature extraction stage mainly consists of two parts: Multiscale wavelet transform and Rotation invarient local binary pattern. The poor quality fingerprints, which are collected through using four different fingerprint sensors in LivDet 2011, are low contrasts between valleys and ridges, so histogram equalization is performed for the fingerprints to improve the contrast between valleys and ridges and extract more useful features. Next we will provide detailed description on related basic knowledge.

### 3.1 Multiscale Wavelet Transform (MWT)

Wavelet transform is one of the most common time-frequency transformation tools to signal processing, image processing. Original spatial siginal is transformed into frequency domain information by using the wavelet transform. The main idea of wavelet transform is that the transform should allow only changes in time extension, but not shape. The wavelet transform can provide us with the frequency of the signals and the time associated to those frequencies, making it very convenient for its application in numerous fields. For instance, signal processing of accelerations for gait analysis [7], for fault detection [8]. For example, during the two-dimensional daubechies transform, the

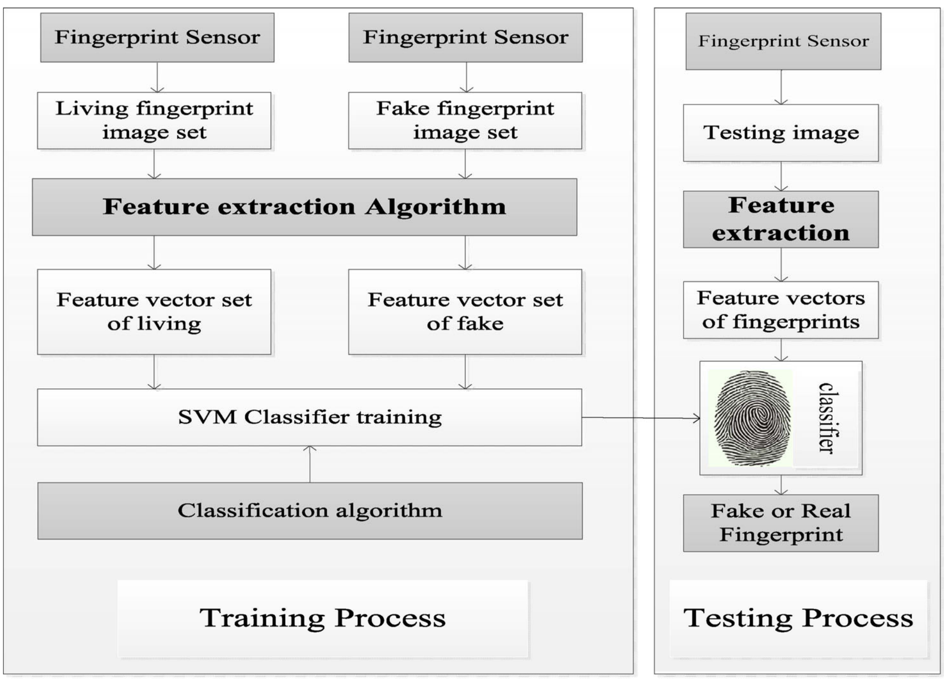



**Figure 2.** The system architecture of our proposed scheme

original siganl $A_k$ (m, n), whose sacle is *k*, is decomposed into four different sub-bands coefficients: approximation low frequency sub-band coefficient $A_{k-1}$(m, n), whose scale is *k*-1 and three high frequency sub-bands coefficients. The horizontal sub-band coefficient is $D^1_{k-1}$ (m, n), the vertical sub-band coefficient is $D^2_{k-1}$(m, n) and the diagonal sub-band coefficient is $D^3_{k-1}$(m, n), all the scales of sub-band coefficients are *k*-1.

In Daubechies algorithm, the equation of the decomposition of multiscale wavelet transformation is as follows:

$$\begin{cases} A_{k-1}(m,n)=\sum_{i,j} h^1_{i-2m} h^2_{j-2n} A_k(i,j) \\ D^1_{k-1}(m,n)=\sum_{i,j} h^1_{i-2m} g^2_{j-2n} A_k(i,j) \\ D^2_{k-1}(m,n)=\sum_{i,j} g^1_{i-2m} h^2_{j-2n} A_k(i,j) \\ D^2_{k-1}(m,n)=\sum_{i,j} g^1_{i-2m} g^2_{j-2n} A_k(i,j) \end{cases} \tag{1}$$

In Equ.1, the scale of wavelet transformation is 1 in our method. The $h^1_{i-2m}$ and $h^2_{j-2n}$ are the high-pass filter, $g^1_{i-2m}$ and $g^2_{j-2n}$ are the low-pass filter of wavelet transformation, in addition, $A_k$ (*i*, *j*) is the original signal and (*m*, *n*) denotes the point coordinate. All the different sub-bands coefficients are related to the wavelet basis functions.

## 3.2 Rotation Invarient Local Binary Pattern (RILBP)

Multiscale Local Binary Pattern (LBP) [9], which can describe the local textural features of given images, is a simple and effective feature extraction algorithm for texture classification. A binary number is obtained by the neighborhood of each center pixel compared with the center vlaues. For example, Figure 3 denotes an example about how to compute a LBP value. Supposing Figure 3 (a) is one part of original image *f*(*x*, *y*), (*x*, *y*) denotes the coordinates of image pixel, and $f_c$ denotes the center pixel value, $f_i$ denotes the neighborhood values of each center pixel, i ∈{1, 2, 3,…, 8}. Threshold comparison has been done. If $f_c >= f_i$, then $g_i$=1. If not, $g_i$=0. Then, we can obtain 8 bits binary streams from Figure 3 (b) after comparison. The upper left corner is the starting position in Figure 3 (b), and we can compute the 8 binary bits stream value according to the clockwise direction. The values corresponding to LBP are computed as following:

$$LBP_{P,R}(x_c, y_c) = \sum_{i=0}^{7} s(g_i, g_c)2^i \tag{2}$$

$$s(z) = \begin{cases} 1, & z \geq 0 \\ 0, & z < 0 \end{cases} \tag{3}$$

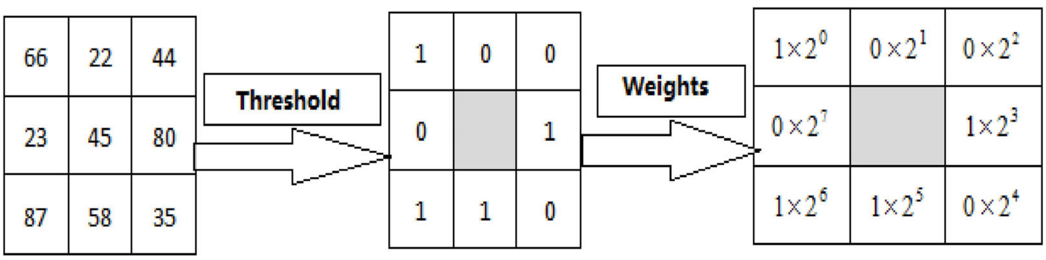
The notation (P, R) will be used for neighborhood pixel values, which mean P are sampling points on a circle when the radius of R in Equ. 2, we can compute the center LBP value: $1\times2^0+0\times2^1+0\times2^2+1\times2^3+0\times2^4+1\times2^5+1\times2^6+0\times2^7=1+8+32+64=105$. Therefore, we can calculate LBP values of the whole image using above steps. Though LBP operator is gray scale invarient, it is not rotation invarient. Once the rotation of the image, we will get a different LBP value. For example, the upper right corner is the starting position in Figure 3 (b), the LBP value corresponding to 8 bits binary stream is $0\times2^0+1\times2^1+0\times2^2+1\times2^3+1\times2^4+0\times2^5+1\times2^6+0\times2^7=2+8+16+64=90$. Thus, we can obtain different LBP values when the images are rotated, and the obtained features are not the ones, which we need. Of course, the final results of classification are wrong. To address above problems, Maenpaa, et al [10] proposed a rotation invarient LBP operator, in which the minimum value is regarded as the LBP value of the neighborhood through continuous rotation of the circular neighborhood to get different LBP values. The equation of rotation invarient LBP is following:

$$\begin{gathered} LBP^{RI}_{P,R}(x_c, y_c) = min(ROR(M) \mid i = 0, 1, ..., p - 1) \\ M = LBP^{RI}_{P,R}, i \end{gathered} \tag{4}$$

In Equ. 4, $LBP^{RI}_{P,R}$ denotes a rotation invarient operator, and the ROR(*x*, *i*) denotes rotation function. That is to say, *x* is moved to the right *i* cycles, (*i* < P). Finally, we can obtain a robust rotation invarient LBP opertor according to the Equ. 4.

## 3.3 Support Vector Machine (SVM)

Nowadays, due to the simplicity of Support Vector Machine, more and more researchers are interested in classifier based on SVM [23]. The SVM method, a supervised machine learning classifier tool, is a




(a) (b) (c)

**Figure 3.** An example of computing the LBP operator

convenient tool for machine learning, pattern recognition and regression analysis problems. The goal of SVM is to obtain a training model, and predict the classification performance by testing fingerprint samples using the svm classifier. LIBSVM software [12] is a classification tools package. When we use SVM, two key issues are needed to be considered.

One problem is concerned about how to select an appropriate kernel function. According to the linear separable and inseparable theory, we can select different kernel functions to achieve classification. Among the kernel functions, the radial basis function (RBF) kernel is appropriate for the two classification problems. Though the class labels and features are all nonlinear, RBF can makes nonlinearly mapping to a high-dimensional space and linear separable in high demensional space. Therefore, due to the advantages of a less complex model and less parameters, RBF kernel function is selected in our method.

Another problem is about how to set an appropriate optimal parameter. Two parameters are needed in the RBF kernel function: $C$ and $\gamma$. In order to obtain a better training model, parameter optimal is necessary before using svm-train.exe executable file. We can find the best classification parameter pairs $C$ and $\gamma$ through using the gunplot.exe executable file and meanwhile train and obtain a training model corresponding to the optimal parameter pair $C$ and $\gamma$. Finally, predicting classification accuracy is better based on the training model.

## 4 Experimental Results

In this section, the performance of our proposed method is estimated by using four different fingerprint sensors in LivDet 2011, such as Biometrika sensor, Italdata sensor, Digital sensor and Sagem sensor. Firstly, we give a brief introduction about the four different fingerprint sensors. Secondly, feature vectors are constructed by using our method and classification is performed using SVM classifier. Then, the validation criterion is introduced, which is used to estimate the performance of algorithm. Finally, the experiments have been done based on four different fingerprint sensors and meanwhile our method has also been compared with the state-of-the art works.

### 4.1 Description of Fingerprints of Different Sensors

Since 2009, to estimate the performance of different fingerprint liveness detection algorithms, the Department of Electrical and Computer Engineering of the Clarkon University (USA) and the Department of Electronic Engineering of the University of Cagliari (Italy) held a LivDet Competition [5]. And the LivDet 2011 databses are divided into two parts: the training set, which is used to train and obtain a training model using the SVM classifier, and a testing set, used to predict the performance of different methods.

Fingerprint images of the LivDet 2011 are collected through using four different optical fingerprint sensors, namely, Digital sensor, Biometrik sensor, Sagem sensor and Italdata sensor. Half of the fingerprints in LivDet2011 are true fingerprints, which are collected from 1000 people alive by using these four fingerprint sensors. The others spoof fingerprints were generated by using five different artificial materials, such as silgum, latex, woodglue, gelatin and ecoflex, and the fake fingerprints are also collected by using four different optical fingerprint sensors, such as Sagem sensor, Biometrika sensor, Itldata sesnor and Digital sensor. More information about the four different sensors is presented in Table 1. From the Table 1, we can clearly observe the resolution, image sizes and the others information corresponding to four different optical sensors. In order to present the real and fake fingerprints corresponding to different sensors and materials, some typical real and fake fingerprints are shown in Figure 4. From the Figure 4, it is hard to distiguish real and fake fingerprints through the human eyes observation. In addition, it is easy for the fingerprint authentication system to be deceived by these fake fingerprints. Therefore, it is necessary to design a better fingerprint liveness detection approach to prevent cheating.

**Table 1.** The detailed characteristics of datasets used in the LivDet 2011

| DATASET | The LivDet2011Database | | | |
|---|---|---|---|---|
| Sensors | Biometrika | Dig.Pers | Italata | Sagem |
| Model No. | FX2000 | 400B | ET10 | MSO300 |
| Res.(dpi) | 500 | 500 | 500 | 500 |
| Image Size | 315×372 | 355×391 | 640×480 | 352×384 |
| Live Fingers | 200 | 200 | 200 | 112 |
| Fake Fingers | 81 | 100 | 81 | 100 |
| Live Subjects | 200 | 1000 | 1000 | 1000 |
| Fake Subjects | 34 | 42 | 34 | 68 |
| Live Samples | 1000 | 1000 | 1000 | 1000 |
| Fake Samples | 1000 | 1000 | 1000 | 1036 |

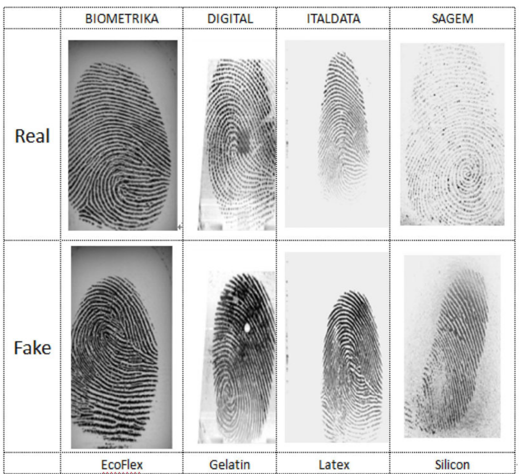



**Figure 4.** Typical real and spoof fingerprints, which can be found in the LivDet 2011

## 4.2 Fingerprint Images Decomposition and Features Extraction

In our method, the extracted features are obtained through using multiscale wavelet transform and rotation invarient LBP. First of all, when a given fingerprint is RGB image, the corresponding to fingerprint images are transformed into gray image and meanwhile histogram equalization is done to enahnce the contrast and extract more useful textural features. Then, the fingerprint images are decomposed into four different sub-bands coefficients through a layer wavelet transform, which are Approximation coefficient, Horizontal coefficient, Vertical Coefficient and Diagonal coefficient respectively. The size of each sub-band coefficient is one quarter of original image. Because the same frequency sub-band coefficients are brought together, the texture fetures can better reflect the properties of the sub-band coefficient. Therefore, the extracted texture features are better than those without wavelet transform decomposition. Next, in order to deal with the rotation change during the communication and extract more robust featrues, rotation invarient LBP operator has been exploited in our method. The detailed description has been given in part 2. We can calculate the texture features corresponding to sub-band coefficients by using Equ. 4 when the P and R are set different parameters.

## 4.3 Classification Performance Metrics and Results

The average error rate has been used to estimate the performance of our method for differetn fingerprint sensors. In Equ.5, the false accept rate (FAR) represents the percentage of fake fingerprints, which are judged as real fingerprint and the false reject rate (FRR) refers to the percentage of real fingerprints being misclassified as fake fingerprint.

$$ACE = (FAR + FRR)/2 , \quad \textbf{(5)}$$

Where in Equ.5,

$$FAR = \frac{Total\ Number\ Imposter\ Fingerprints\ Accepted\ as\ Genuine}{Total\ Number\ of\ Forgery\ Tests\ Performed}, \quad \textbf{(6)}$$

$$FRR = \frac{Total\ Number\ Genuine\ Fingerprints\ Accepted\ as\ Imposter}{Total\ Number\ of\ Genuine\ Matching\ Tests\ Performed}, \quad \textbf{(7)}$$

In order to show our classification accuracy is better for different fingerprint sensors, training process and testing process are included in our method.

**Process 1.** Training process. To detect the liveness of fingerprint and enhance the classification accuracy for different fingerprint sensors, it is necessary to obtain an optimal training model according to texture features vectors. Firstly, fingerprint image pre-processimg is necessary in our experiment, and the image gray transform and images histogram equalization are included in the process of pre-processing. Then, the given fingerprint images are decomposed into four different sub-band coefficients through a layer of wavelet transform. The four different sub-band coefficients are approximation coefficient in low frequency domain and three sub-bands coefficients in high domain, which are horizontal coefficient, vertical coefficient and diagonal coefficient respectively. Next, the feature vectors are constructed by using rotation invarient LBP codes according to the Equ.4, and feature vector of each sub-band coefficient is composed of 256 features through statistical gray histogram. In order to gain a better training model and make the predication more accuracy, parameter optimization is vital step. For different parameter pairs (P, R), the ACE is different for different fingerprint sensors. Thus, to find the optimal parameter pairs (P, R), a lot of experiments have been done in our method. The best parameter pair (P, R) and the ACEs of several other parameter pairs have been shown in Table 2. Finally, a better training model has been trained by using executable file svm-train tool in SVM classifier to train the feature vectors, which are obtained using our proposed method.

**Table 2.** The optimal parameter pair (P, R) in LivDet 2011 for different fingerprint sensors

| Optimal parameter pair (P, R) | The Average Classification Error ACE in (%) | | | | |
|---|---|---|---|---|---|
| | Biometrika | Digital | Italdata | Sagem | Average |
| (16,1) | 7.45 | 5.75 | 23.05 | 4.92 | 10.29 |
| (16,2) | 6.65 | 3.7 | 10.6 | 3.36 | 6.08 |
| (8,1) | 11.75 | 4.55 | 20.2 | 6.34 | 10.71 |
| (8,2) | 12.9 | 6.7 | 17.15 | 7.13 | 10.97 |

**Process 2.** Testing process. After the process 1, we can extract the textural feature vectors through using our method and meanwhile get a better training model. In the process 2, the predication of classification accuracy will be performed through using the svm-predict tool in the SVM classifer. Both in the Testing process and Training process, they are performed on MATLAB R2010a and Windows 7 operating system. In our experiment, the classification accuracy of ACE, which is obatined through using Equ.5, Equ.6 and Equ.7, and these results of others' methods are shown in Table 3. In addition, to facilitate the readers to observe, the best values obtained are highlighted in bold in Table 3. From the Table 3, we can observe that the ACE of our

**Table 3.** Comparison of ACE in the LivDet 2011 for differnet fingerprint sensors

| Methods | The Average Classification Error (ACE) (%) For Different Sensors | | | | |
|---|---|---|---|---|---|
| | Biometrika | Digital | Italdata | Sagem | Average |
| Our method | 6.65 | 3.7 | 10.6 | 3.36 | 6.078 |
| LBP [18] | 11.0 | 10.6 | 19.0 | 8.4 | 12.3 |
| MLBP[16] | 7.3 | 2.5 | 14.8 | 5.3 | 7.5 |
| WLD[14] | 13.3 | 13.8 | 27.7 | 6.7 | 15.4 |
| LPQ[19] | 12.8 | 9.7 | 15.6 | 6.3 | 11.1 |
| WLD+LPQ[15] | 7.3 | 8.1 | 12.7 | 3.7 | 7.9 |
| LPB PCA SVM[20] | 8.2 | 3.85 | 23.68 | 5.56 | 10.32 |
| Dermalog [5] | 20 | 36.1 | 21.8 | 13.8 | 22.93 |
| Federico [5] | 40 | 8.9 | 40 | 13.4 | 25.57 |
| LPB PCA SVM[17] | 8.2 | 3.85 | 23.68 | 5.56 | 10.32 |
| BSIF [11] | 6.8 | 3.5 | 13.6 | 4.9 | 7.2 |
| OCSNE [21] | 9.8 | 36.6 | 23.5 | 24.4 | 23.6 |
| Best Result in LivDet2011[5] | 20 | 36.1 | 21.8 | 13.8 | 22.93 |

method for the four different sensors is the lowest. It shows that detection accuracy of our method is the best algorithm. In addition, the classification error for the different sensor except Digital optical sensor, our proposed method is the best when using the same fingerprint sensor. All at once, comparing with the latest references, the ACE of our method is obviously superior to others' methods.

## 5 Conclusions and Future Works

A new fingerprint livness detection approach based on multiscale wavelet transform and rotation invarient LBP has been proposed in this paper. As illustration in our system architecture, the databases are collected by using four different fingerprint sensors. Before constructing the feature vectors, the preprocessing operation is necessary. Then the texture features are extracted by using our method. A training model is trained by using the svm-train tool in SVM classifier. With the help of the trained model, we can predict the classification accuracy of testing samples. For the four different fingerprint sensors, the experimental result has shown that ACE of our method is the lowest and meanwhile proves its ability to adapt to all rotation invarient and gray invarient image attacks. In addition, our method is a software-based solution, which distinguishes real or fake fingers only based on analysing fingerprint textural features and not on other physiological measures captured by special hardware devices. Our method, such as the one presented in this work, is of great importance in the biometric field as they are more robust to prevent image rotation attacks and meanwhile enhance the security of authentication systems. In addition, the ACE of our merhod is the best and meanwhile our method is better than others' methods except Digital Sensor when we using the same fingerprint sensors.

The classification accuracy is extremely affected by the noise. Therefore, in order to reduce the influence of different noise, median filter is applied in our future work and meanwhile we will extract features to detect the liveness of fingerprint by using two layers or more layers wavelet transform. The classification accuracy is higher when the testing fingerprints corresponding to optical fingerprint sensor is predicted, whether the ACE of our method is the best or not when the testing fingerprints databases are estimated under different optical fingerprint sesnors. Therefore, the cross validation for different fingerprint sensors will be significant. All these will be done in our future works.

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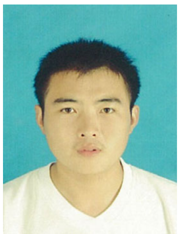
## Biographies



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