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WAVELET PYRAMID BINARY PATTERNS FOR FINGERPRINT LIVENESS DETECTION

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Abstract

In this paper a new feature vector, Wavelet Pyramid Based Binary Patterns (WPBP), is evaluated for Fingerprint Liveness Detection (FLD). It consists of two components: the first component involves detection of key points from four levels of pseudo-Laplacian pyramid obtained using Discrete Wavelet Transform (DWT) and their description using Local Binary Patterns (LBP) to represent multi-scale texture features; the second component consists of detection of shape, size and intensity variant features from first level wavelet approximation band. The features are then represented using Completed Local Binary Pattern (CLBP) descriptor. The combined feature vector is classified using Radial Basis Function (RBF) kernel Support Vector Machine (SVM) classifier. The proposed feature vector has been investigated for FLD on LivDet 2009, 2011, 2013 and 2015 competition databases. Experimental results demonstrate that the proposed feature vector is effective for FLD. The proposed feature vector is of reduced dimension, easy to implement and has good discrimination capability.

Keywords:

Fingerprint Liveness Detection, Discrete Wavelet Transform, Pseudo-Laplacian Pyramid, Completed Local Binary Pattern

1. INTRODUCTION

Biometrics refers to an automatic recognition of individuals based on their physical or behavioral characteristics [1]. Fingerprint is a mature, and most commonly used biometric due to uniqueness, permanence and ease of use [2]. Mobile payments, Attendance monitoring systems are few examples where fingerprint based systems are deployed. Nonetheless, they have found to be vulnerable to presentation attacks via an artificial replica of a live finger, called spoof, which is created from Gelatine, Silicone etc. [3].

FLD has attracted attention of researchers to safeguard security of biometric systems to utilize their full capacity. Hardware based solutions are expensive due to additional devices to sense vitality characteristics like temperature, pulse Oximetry [4], [5]. Dynamic software based methods observe changes in image properties over a period of time due to Physiological or Biological phenomenon like perspiration, skin distortion [6] [7]. They are time consuming and hence it needs operational expert. Static software based methods extract discriminatory features from a single image and are inexpensive, non-invasive, user friendly and autonomous. Images from live and spoof fingers differ in their textural characteristics.

The success of FLD system lies in capturing these differences to discriminate a live finger from a spoof. A number of features have been crafted or adopted for this purpose. Many of them are concatenation of features that characterize shape, size, texture and gradients and often have large feature dimension. Based on our observations, highly discriminatory features of reduced dimension would be desirable. High dimensional features suffer from high computational cost and memory usage.

The work in this paper presents a new feature vector consisting of two components for FLD. The first component consists of detection of key points from four levels of pseudo-Laplacian wavelet pyramid, obtained using DWT instead of using Gaussian filters, to extract multi-scale texture features, which are then represented by conventional LBP descriptor. The second component includes features from first level wavelet approximation band to represent the shape, size and texture, described using CLBP descriptor. The histograms of both the descriptors are concatenated to form the final feature vector named as Wavelet Pyramid Binary Patterns (WPBP). The experimental results indicate that the proposed feature vector has high discrimination capability in spite of being simple and of reduced dimension.

2. LITERATURE REVIEW

The focus of this paper is on FLD using static, single image-based software approach. The methods from literature are classified into four types: pore based, quality-based, global feature-based and local feature-based. A live finger is characterized by the presence of pores along the ridges which are somewhat circularly shaped and can be open or closed. The sweat from pores spreads across and along the ridges causing variations in intensity patterns in the acquired images. Marcialis et al. [8] performed an analysis of location and number of pores. Manivanan et al. [9] identified only open pores based on the perspiration activity using high pass and correlation filtering. Johnson and Schuckers [10] detected active pores and analyzed the surrounding region to detect the perspiration activity. These methods require high-resolution sensor and fail when spoofs are of good quality. Live and spoof finger images differ in terms of blurriness, clarity of ridge-valley structure and noise which cannot be detected by human eyes. Quality based methods, crafted features to detect these differences. Moon et al. [11] performed the wavelet transform based de-noising and found that noise residue is higher in spoof images. Galbally et al. [12] crafted ten features to assess the quality of the ridge-valley structure. Feature selection technique was employed to reduce feature dimension. Galbally et al. [13] further adopted features from full reference Image Quality Assessment method for FLD. These methods are likely to suffer from the availability of high-resolution spoof images of better quality.

FLD is essentially a pattern recognition problem. To achieve better results, global level features of large dimension are derived and fed to a classifier algorithm. Abhyankar and Schuckers [14] derived multi-resolution texture features which were discriminatory due to inherent texture and density differences between live and spoof images. Global features represent entire image with a single feature vector. Even though they result in compact representation of an image, they are unlikely to produce better results due to nature of information contained in them.

Recently, local features based methods from Machine Vision field are investigated for FLD. Local features are derived from multiple locations in an image and are likely to provide discriminatory information about the image. Image is decomposed into small patches to compute features and is represented by a histogram of feature descriptors. Ghiani et al. [15] quantized and encoded phase information in local patches and named it Local Phase Quantization (LPQ). Gragnaniello et al. [16] proposed Weber Local Descriptor (WLD) containing information about local contrast and orientation. These methods offered moderate results on LivDet datasets. The same authors introduced Local Contrast Phase Descriptor (LCPD) formed with local phase information and a modified differential excitation component of WLD [17]. The results obtained on the LivDet 2011 dataset are superior. Jia et al. [18] applied multi-scale LBP to extract multi-scale features from a region instead of a single target pixel. The radii of the region were found by cross-validation. The DWT is widely used in the literature due to spatio-frequency localization and multiresolution capability. Kundargi and Karandikar [19] proposed a feature vector consisting of encoded DWT coefficients of low-frequency approximation band and high-frequency detail subbands using CLBP descriptor. Even though computationally simple, promising results are reported on the LivDet dataset due to better discrimination capability of the features. Kim [20] proposed Local Coherence Patterns (LCP) to encode differences in coherence patterns. The authors observed that the non-uniform surface of spoof fingers causes the difference of dispersion in the image gradient field between live and fake finger images. Dubey et al. [21] proposed a combination of oriented gradient features and texture features with an ensemble of various classifiers, multiple voting schemes and employed dynamic threshold selection. The method performed well on LivDet datasets. Xia et al. [22] proposed Weber Local Binary Descriptor (WLBD), consisting of modified differential excitation and gradient orientation components.

3. PROPOSED METHOD

The block diagram of the proposed method for FLD is shown in Fig.1. To discriminate the images from live and spoof fingers, it is essential to combine information from global level features and multiscale texture features. Global level features convey information related to shape, size and gray level spatial distribution. The multi-scale image representation allows to analyze texture features at different scales. Motivated by this observation, a feature vector is proposed consisting of two components, to represent global and multiscale texture features respectively. First key point based texture features are described which represent multi scale local image properties, leading to compact and discriminatory image representation. The objective is to capture discriminatory texture features at key points selected from different scales for FLD.

3.1 PSEUDO-LAPLACIAN WAVELET PYRAMID AND IDENTIFICATION OF KEY POINTS

Image representation using pyramid supports image analysis at multiple scales [23]. Laplacian pyramid of bandpass images is obtained by subtraction of each low pass image from the next level low pass image, both interpolated to the size of original image. Laplacian pyramid has an important property that it is a complete image representation. It enhances texture features at various scales for scaled image analysis. Pyramid constructed using DWT is referred to as pseudo-Laplacian pyramid [24]. In the proposed work two dimensional DWT is used for pyramidal image representation [25]. To begin with, each fingerprint image is converted to gray scale format as only intensity information is used for further analysis. The two dimensional DWT is applied to decompose image upto L=4 levels. This process generates one low frequency approximation band LL_i, i=1,2,3,4 and three high frequency detail subbands LH_i, HL_i, sHH_i, i=1,2,3,4, at each level of decomposition i.

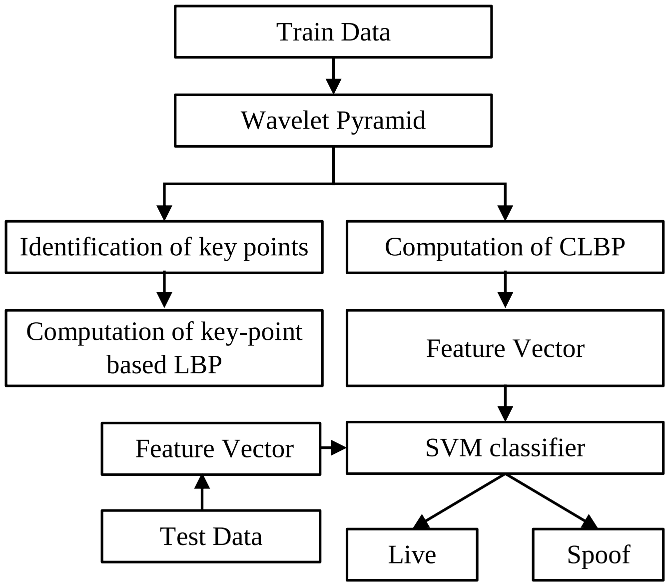


Fig.1. Block diagram of the proposed method for FLD

In this paper DWT is implemented using Haar wavelet due to its fast speed and the fact that approximation bands generated by Haar and Daubechies wavelets are very much similar, which is also reported in earlier study [26] [27]. Each of the four approximation bands LL_i, is interpolated to the size of the original image. Eq.(1) represents this process:

$$I\left(LL_i\right)=\left(LL_i \uparrow 2^i\right) \quad (1)$$

Here $\uparrow 2^i$ represents interpolation operation by a factor of 2^i for approximation band at decomposition level $L=i$. The set of signals in Eq.(1) along with the original image $x(m,n)$; ($y_0(m,n)$ = $x(m,n)$); are then used to generate pseudo-Laplacian pyramid, consisting of W_i, as shown by Eq.(2):

$$W_i\left(m,n\right)=y_{i-1}\left(m,n\right)-y_i\left(m,n\right) \quad i=1,2,3,4 \quad (2)$$

where $y_i(m,n)$, i=1,2,3,4 represents approximation band at each level of decomposition.

The key points are located at each (m,n) position by selecting maximum value of $W_i(m,n)$, i=1,2,3,4. These points represent the salient information representative of the texture beneath. The Fig.2(a) illustrates a two-level DWT decomposition. The Fig.2(b) represents the process to locate key points from four levels of pseudo-Laplacian wavelet pyramid. It is to be noted that level 1 contains keypoints detected in W_1, level 2 contains keypoints detected in W_1 and W_2 , level 3 contains keypoints detected in W_1, W_2 and W_3 and level 4 contains keypoints detected in W_1, W_2, W_3 and W_4. The decomposition is performed upto level four since the higher level decomposition results in blurred image which loses its characteristic properties due to distorted ridge-valley structure. In our experimentation, stable results were observed after third or fourth level. Each detected key point has a level in multiscale pseudo-Laplacian pyramid and is representative of local texture information of that level.

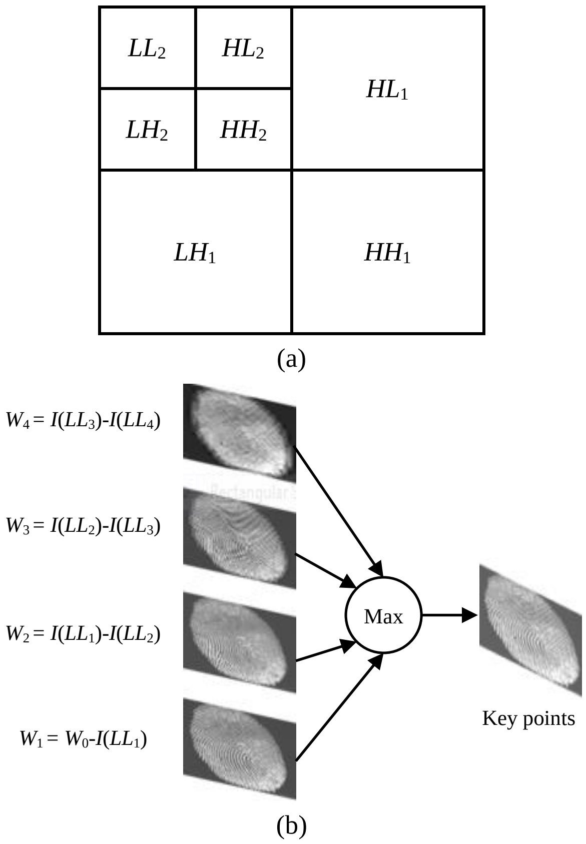


Fig.2(a). Illustration of 2-level DWT (b) Procedure to locate key points from pseudo-Laplacian pyramid

The detected key points are then carried forward to the next stage of processing.

3.2 COMPUTATION OF KEY POINT BASED LBP

The LBP descriptor is very simple and has been used extensively for texture analysis in computer vision field [28]. It represents the local texture features of an image by comparing the difference between the values of the central pixel and its neighbouring pixels. It has an important property of being illumination invariant. In the proposed work original LBP descriptor is employed due to its computational simplicity, defined over window of size (3×3) around the central pixel and value of central pixel acts like a threshold. The LBP descriptor encodes local information around the central pixel as a decimal number in binary format described by Eq.(3):

$$LBP_{1,8} = \sum_{i=0}^{7} s\left(g_i - g_c\right)2^i,\ s\left(v\right) = \begin{cases} 1 & v \geq 0 \\ 0 & v < 0 \end{cases} \tag{3}$$

Here g_c represents gray scale value of the central pixel and g_i represents gray scale value of the surrounding 8 pixels separated by a radius of one unit. In the proposed work the LBP values computed at only the selected key points at four levels of pyramid are considered. All these LBP values are combined together instead of serial concatenation of LBP histograms of each level. The histogram of all these LBP values, of dimension 256, forms the first component of the proposed feature vector. The uniform and rotation invariant version of LBP was not selected as it was found that it did not contain enough discriminatory information for FLD purpose due to small bin size.

3.3 COMPUTATION OF CLBP

Earlier studies show that the global information of texture features play a significant role in fingerprint image characterization [27]. Random ridge valley structure, skin elasticity and the presence of pores and sweat, cause significant wide and random gray level variations in a live finger image. While a spoof finger cannot experience sweat, has a regular ridge valley structure, resulting in a few gray level variations in the acquired image. This difference in spatial distribution of gray levels is represented by texture features and plays important role to characterise live and spoof images for FLD. The first level low frequency approximation band obtained from wavelet decomposition retains global level ridge structure characteristics and the texture related information. It possesses high energy among other low frequency approximation bands. It represents the denoised basic figure of the original fingerprint image and hence is the most informative with the highest discriminative power. Consequently texture features are extracted from first level approximation band LL_1. Based on the study in [19] CLBP descriptor is used as it has proved to possess higher discrimination capability for FLD. Completed Local Binary Pattern Descriptor proposed by Guo et al. [29] is a modified version of original LBP. CLBP encodes sign (S) and magnitude (M) of the local differences obtained by employing local difference sign magnitude transform (LDSMT):

$$d_i = g_i - g_c = s_i * m_i,\ and \begin{cases} s_i = sign\left(d_i\right) \\ m_i = \left|d_i\right| \end{cases} \tag{4}$$

where, m_i and $s_i = \begin{cases} 1 & d_i \geq 0 \\ 0 & d_i < 0 \end{cases}$ represents magnitude and sign of local difference, d_i, respectively.

The CLBP_Sign (CLBP_S) and CLBP_Magnitude (CLBP_M) convey sign and magnitude related to the local texture information. In addition, CLBP_Center (CLBP_C) operator is formed by encoding central pixel into binary code using mean gray level of whole image as a global threshold. The three operators are combined jointly to form a three dimensional histogram. Uniform and rotation invariant form of CLBP defined over a local patch of (3×3) with a radius of one unit from the central pixel, $CLBP_{1,8}^{riu^2}$ is applied to LL_1 approximation band to describe global features. This forms the second component of the proposed feature vector of dimension 200. The two components are concatenated to form a combined feature vector of dimension

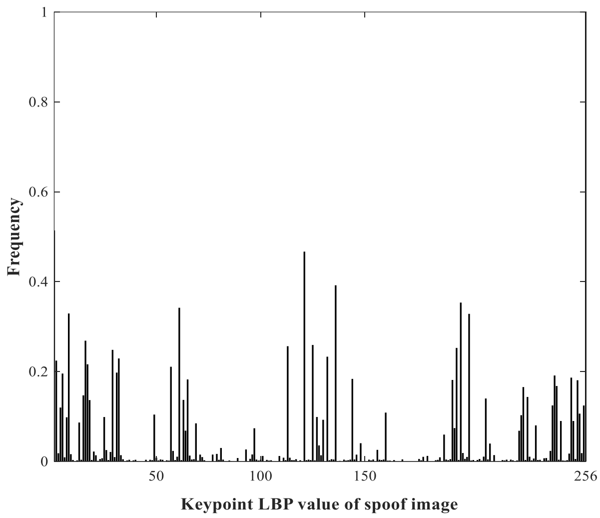
456, named as Wavelet Pyramid Binary Patterns (WPBP). To demonstrate the effectiveness of the proposed feature vector, histogram of both descriptors for a spoof and a live image are presented in Fig.3. It can be observed that the proposed feature vector exhibits observable differences for a spoof and live finger to demonstrate its discrimination capability.

4. EXPERIMENTAL RESULTS

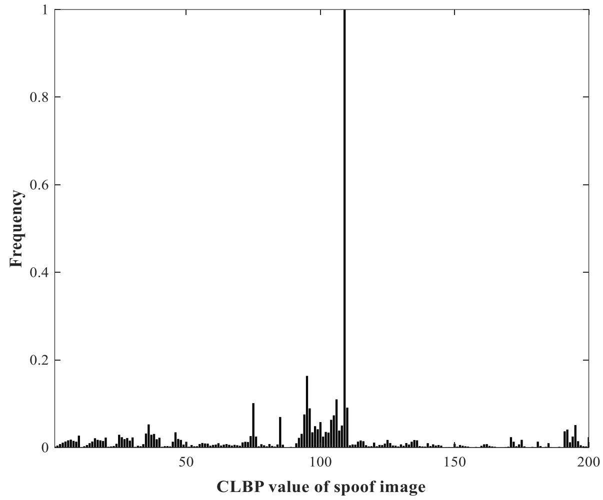
The evaluation of the proposed method for FLD is presented and comparison with the existing methods is presented.

4.1 DATABASE DESCRIPTION

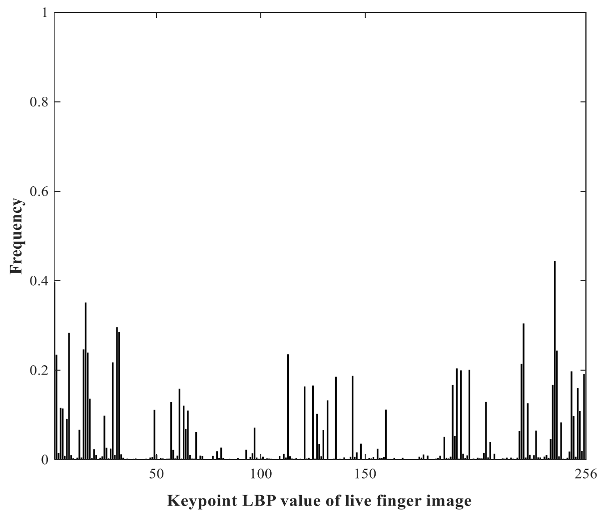
Results are presented on four openly available databases released for FLD competitions, LivDet 2009 [30], LivDet 2011 [31], LivDet 2013 [32] and LivDet 2015 [33], by Clarkson University and University of Cagliari. Optical sensors are used in all the databases. The database of each sensor has a separate and non-overlapping train data and test data. Except for Biometrika and Italdata sensor of LivDet 2013, spoof fingers for all other databases were collected using co-operative method and hence are more challenging. LivDet 2015 test database consists of images of spoof material not present in train data. The details of these databases are provided in Table.1.



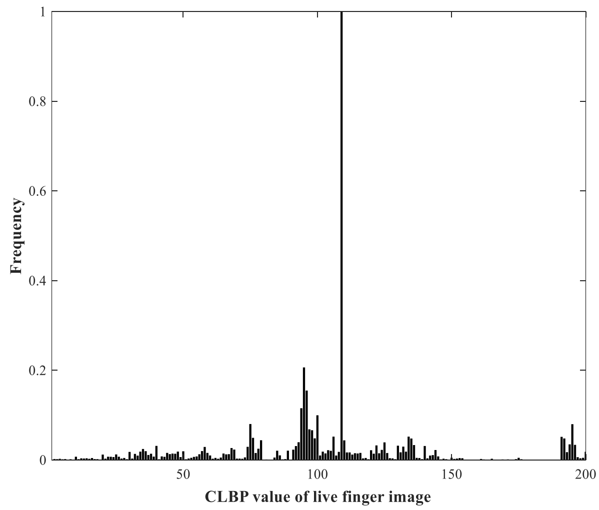
(a)



(b)



(c)



(d)

Fig.3. Proposed WPBP feature values calculated for a spoof and live finger image

4.2 CLASSIFIER

The experiments are conducted using SVM classifier from LIBSVM [34] with radial basis function (RBF) kernel. The tuning parameters of RBF kernel SVM are obtained by ten-fold cross validation on training data.

SVM classifier, assumes that the data is in the range [0,1]. Hence, each dimension of the feature vector of training dataset is normalized using Eq.(5):

$$FV_n = \frac{FV - FV_{\min}}{FV_{\max} - FV_{\min}} \tag{5}$$

where FV_{min} and FV_{max} represent minimum and maximum value, of each dimension of feature vector FV, respectively. These values are stored to normalize corresponding dimensions of feature vectors of test data before they are applied to the SVM classifier.

5. RESULTS AND COMPARISON

Average Classification Error (ACE) is used as a metric to evaluate our proposed method. It is defined as

$$ACE = \frac{FLR + FFR}{2} \tag{6}$$

Table.1. Details of LivDet 2009, LivDet2011, LivDet2013 and LivDet2015 Databases

Database	Sensor (Optical)	Model No.	Res. (dpi)	Image size	#Live images Train/Test	#Spoof images Train/Test	Coop. method.
LivDet2009 [30]	Biometrika	FX2000	569	312*372	520/1473	520/1480	Yes
	CrossMatch	Verifier 300 LC	500	640*480	1000/3000	1000/3000	Yes
	Identix	DFR 2100	686	720*720	750/2250	750/2250	Yes
LivDet2011 [31]	Biometrika	FX2000	500	312*372	1000/1000	1000/1000	Yes
	Dig. Pers	400B	500	355*391	1000/1000	1000/1000	Yes
	Italdata	ET10	500	640*480	1000/1000	1000/1000	Yes
	Sagem	MSO30	500	352*384	1000/1000	1000/1000	Yes
LivDet2013 [32]	Biometrika	FX2000	569	312*372	1000/1000	1000/1000	No
	Italdata	ET10	500	640*480	1000/1000	1000/1000	No
LivDet2015 [33]	Biometrika	HiScan- PRO	1000	1000*1000	1000/1000	1000/1500	Yes
	CrossMatch	L Scan Guardian	500	640*480	1510/1500	1473/1448	Yes
	Dig. Pers.	U. are U. 5160	500	252*324	1000/1000	1000/1500	Yes
	GreenBit	DactyScan 26	500	500*500	1000/1000	1000/1500	Yes

The False Living Rate (FLR) represents the percentage of spoof fingerprint images misclassified as live and the False Fake Rate (FFR) represents the percentage of live fingerprint images misclassified as spoof.

The experiments on four LivDet databases revealed that the results were stable at either third or fourth level of the pyramid, for the majority of the sensors. Hence experiments were performed upto four levels. The Table.2 - Table.5 shows the ACE values at second, third and fourth levels of pyramid, respectively. For most of the sensors better performance is achieved at level 4. It is so because at level 4 LBP values derived from key points detected from W 1 to W 4 are accumulated.

Table.2. ACE on three sensors of LivDet 2009 database

LivDet 2009 Sensor	ACE (%)		
	Pyramid level		
	2	3	4
Biometrika	4.91	4.64	4.64
CrossMatch	5.65	5.72	5.72
Identix	1.04	1.04	1.04

Table.3. ACE on four sensors of LivDet 2011database

LivDet 2011 Sensor	ACE (%)		
	Pyramid level		
	2	3	4
Biometrika	5.75	5.75	5.75
Dig. Pers.	2.6	2.35	2.4
Italdata	15.55	15.3	15.3
Sagem	5.8	5.65	5.65

Images from different sensors belong to different file formats, have different resolution and sizes. It is required to have a feature vector to extract the differences in the properties of live and spoof finger images for FLD. It is also the reason for variable performance of the proposed method on different sensors.

Table.4. ACE on two sensors of LivDet 2013 database

LivDet 2013 Sensor	ACE (%)		
	Pyramid level		
	2	3	4
Biometrika	3.45	3.35	3.35
Italdata	6.2	6.1	6.1

Table.5. ACE on four sensors of LivDet 2015 database

LivDet 2015 Sensor	ACE (%) Pyramid level		
	2	3	4
Biometrika	13.08	13.24	12.96
CrossMatch	0.20	0.20	0.20
Dig. Pers.	14.8	14.52	14.52
GreenBit	9.08	9.16	9.16

The results indicate that the performance of most of the sensors is better at level 4 since the sufficient number of feature descriptors are present at this level. Henceforth the proposed feature, WPBP, is the one which is computed at level 4 of pyramid and classified using RBF kernel SVM. The comparison of our result on LivDet 2009 database with other methods is presented in Table.6. It can be seen that our result outperforms others and is consistent over all the three sensors of LivDet 2009 database. Table.7. provides comparison with others on LivDet 2011 database. It is considered to be a challenging database. Our method performs quite well and has obtained the best result for Digital Persona [31] sensor. The results are better than those obtained with single feature in the works of [21] wherein authors have used multiple features, classifiers, voting techniques and dynamic threshold selection techniques. Results for LivDet 2013 are presented in Table.8. It can be seen that our method has obtained moderate results. This can be attributed to the fact that the same tuning parameters of RBF kernel SVM are used for all the sensors in all the four databases. This has resulted in compromising accuracy of some sensors. It is to be noted that except LivDet 2013 all other three involve co-operative method of image acquisition. The Table.9 presents results on LivDet 2015 database. As reported earlier the test data of this database consists of images of spoof material not present in train data. Our method has performed quite well and has obtained the best result for CrossMatch sensor [33].

Table.6. Comparison of ACE on LivDet 2009 database

Method	Sensor, LivDet 2009			Average ACE
	Biometrika	CrossMatch	Identix	
WPBP proposed method	4.64	5.72	1.04	3.8
LCP [20]	13.21	15.58	10.71	13.17
LBP [28]	13.51	20.32	10.78	14.87
LPQ [15]	21.13	33.33	29.8	28.09
Quality based [12]	1.73	11.15	6.87	6.58
LivDet2009 Comp. Winner [30]	18.15	9.4	2.75	10.1

It is to be noted that the results of winner of LivDet 2015 competition [33] are obtained using neural network. The average ACE by our method is better than fifth winner of LivDet 2015. Our results are better than that of WLBPD [22] descriptor which has performed quite well on LivDet 2011 and LivDet 2013 databases. This indicates that our proposed method has good generalization capability. In Table.10 ACE is compared with state-of-art methods for LivDet 2009, LivDet 2011 and LivDet 2015 databases. LivDet 2013 database is not considered since individual results of sensors are not reported for few methods. It is to be noted that the best results are highlighted in these tables.

Table.7. Comparison of ACE on LivDet 2011 database

Method	Sensor, LivDet 2011				Ave. ACE
	Biometrika	Dig. Pers.	Italdata	Sagem	
WPBP proposed method	5.75	2.4	15.3	5.65	7.28
WLBPD [22]	5.65	4.1	11.85	2.25	5.96
Dubey's method [21]	7.89	6.25	8.1	5.36	6.9
LCPD [9]	4.9	4.2	11	2.7	5.7
MSLBP1 [18]	7.3	2.5	14.8	5.3	7.48
MSLBP2 [18]	10.6	6.7	12.6	5.6	8.88
LPQ [15]	14.7	12	14.4	8	12.3
WLD [16]	13.25	13.75	27.67	6.66	15.33
LCP [20]	--	--	--	--	33.21
LBP [28]	13.0	10.8	24.1	11.5	14.85
Winner, LivDet 2011 [31]	20.0	36.1	21.8	13.8	22.93

Table.8. Comparison of ACE on LivDet 2013 database

Method	Sensor, LivDet 2013		Average ACE
	Biometrika	Italdata	
WPBP proposed method	3.35	6.1	4.73
WLBPD [22]	0.4	0.95	0.68
Dubey's method [21]	2.27	2.17	2.22
LBP [28]	1.6	3.0	2.3
WLD [16]	5.2	7.1	6.15
LivDet2013 Comp. Winner [32]	1.7	0.8	1.25

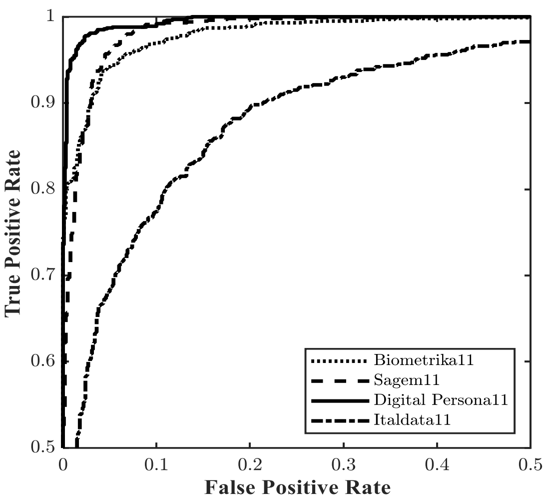
Table.9. Comparison of ACE on LivDet 2015 database

Method	Sensor, LivDet2015				Ave. ACE
	Biometrika	Cross Match	Dig. Pers.	Green Bit	
WPBP proposed method	12.96	0.20	14.52	9.16	9.21
WLBPD [22]	9.64	10.82	13.72	4.53	9.68
LBP [28]	13.48	11.46	14.44	7.88	11.82
LCP [20]	18.44	16.79	20.44	12.11	16.95
WLD [16]	20.76	10.82	13.72	4.53	9.68
LivDet 2015 Comp. Winner [33]	6.28	1.9	5.64	4.6	4.61

The experiments explored in this section conveyed promising results for FLD. The proposed feature vector has proved to be of high discriminatory capability as noticed from experiments on four benchmark databases consisting of more than 50,000 images. The use of Haar wavelet transform has resulted in fast computations. In this work common SVM parameters, obtained by 10-fold cross-validation, are used for each sensor of all the four databases. It is required to improvise the proposed method to match FLD performance comparable to the state-of-art methods. In addition, modification in the proposed method is needed for intra-database cross-sensor and inter-database cross-sensor FLD performance evaluation as a part of the future work. The proposed method has the drawback of comparatively higher computational complexity compared to conventional approach due to key-point extraction approach. Overall it can be seen that the proposed method assuredly performs the task of FLD. The Receiver Operating Characteristic curves of all databases are presented in Fig.5.

Table.10. Comparison of Average ACE on LivDet databases

Method	**LivDet 2009**	**LivDet 2011**	**LivDet 2015**	**Average ACE**
WPBP proposed method	3.8	7.28	9.21	6.76
LCP [20]	13.17	33.21	13.61	20.00
LBP [28]	14.87	31.81	15.16	20.61
LPQ [15]	28.09	28.74	34.17	30.33
LivDet Comp. Winner [30] [31] [33]	10.1	22.93	4.61	12.55



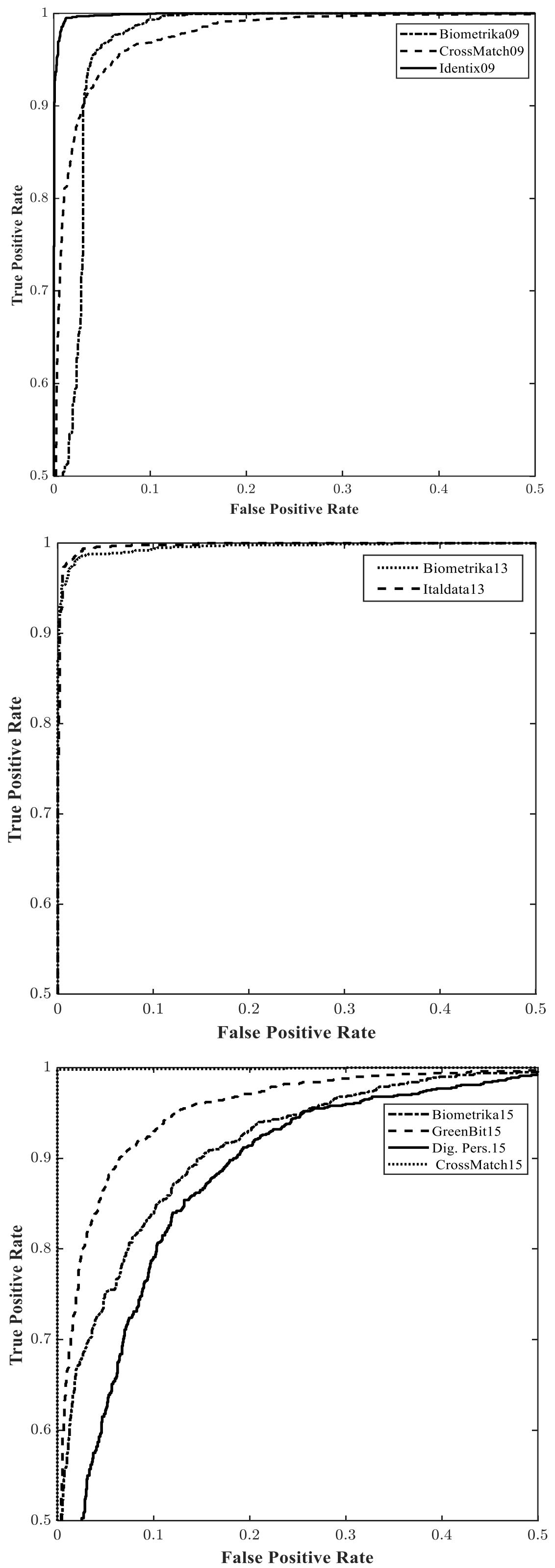


Fig.4. Receiver Operating Characteristics of LivDet databases

From Fig.4, it is obvious that further exploration is a must of our proposed features for effective FLD.

6. CONCLUSION

In this paper, a new method is proposed to detect liveness from a fingerprint image. The proposed feature vector consists of two components, CLBP descriptor of first level DWT approximation band and LBP descriptor computed at key points of DWT pyramid. The method has been tested for four benchmark databases consisting of more than 50,000 images altogether. The performance of the proposed method has been compared with the existing methods in terms of average classification error. The proposed method does not involve any pre-processing of the images and due to moderate feature dimension does not require use of feature selection or dimension reduction techniques. The proposed method has provided improved results on all four databases with common tuning parameters of RBF kernel SVM. The significance of the proposed method can be attributed to higher discrimination capability of the feature vector and simplicity of the feature vector. The feature vector is able to capture differences in shape, size and texture patterns of live and spoof fingerprint images for effective fingerprint liveness detection.

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