B.TECH. PROJECT REPORT

On

Fingerprint Anti-spoofing Using Various Texture-based Features

BY

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DISCIPLINE OF COMPUTER SCIENCE AND ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY INDORE

November 2018

Fingerprint Anti-spoofing Using Various Texture-based Features

A PROJECT REPORT

Submitted in partial fulfillment of the requirements for the award of the degrees

Of
BACHELOR OF TECHNOLOGY
In

COMPUTER SCIENCE AND ENGINEERING

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INDIAN INSTITUTE OF TECHNOLOGY INDORE
November 2018

CANDIDATE'S DECLARATION

I hereby declare that the project entitled **"Fingerprint Anti-spoofing Using Various Texture-based Features"** submitted in partial fulfillment for the award of the degree of Bachelor of Technology in 'Computer Science and Engineering' completed under the supervision of **Dr. Somnath Dey (Assistant Professor, Computer Science and Engineering),** IIT Indore is an authentic work.

Further, I declare that I have not submitted this work for the award of any other degree elsewhere.

Dip Kumar Das

CERTIFICATE by BTP Guide(s)

It is certified that the above statement made by the students is correct to the best of our knowledge.

Dr. Somnath Dey,
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PREFACE

This report on "Fingerprint Anti-spoofing Using Various Texture-based Features" is prepared under the guidance of Dr. Somnath Dey, Assistant Professor, Computer Science and Engineering, IIT Indore.

Through this report, I have tried to provide a detailed description of software-based liveness detection of fingerprint images and extraction of various textural features. I have tried to minimize the average classification error using different textural features for fingerprint liveness detection. Experimental results are also evaluated for feature fusion, cross-dataset, and cross materials scenarios. A comparative study is also performed with some of the well known fingerprint liveness detection techniques. I have tried to the best of my abilities and knowledge to explain the content in a lucid manner.

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ACKNOWLEDGMENTS

I wish to thank Dr. Somnath Dey for his kind support and valuable guidance throughout the duration of the project, giving me an opportunity to work at my own pace, while providing me with very useful directions whenever necessary.

I wish to express my sincere gratitude to Mr. Ram Prakash Sharma for his guidance throughout the project and helping me on the concerned topics.

I also thank Mr. Prakash Choudhary for helping me on the concerned topics.

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ABSTRACT

In this report, experimental results of the fingerprint liveness detection using various texture features (curve-let, BSIF, LCPD, LPQ, etc.) are evaluated. The results are evaluated on publically available LivDet databases (2009, 2011, 2013, and 2015). Five different classifiers i.e., SVM, Decision Tree, Random Forest, Tree Ensemble, and PNN are used for the performance evaluation of the curvelet-based anti-spoofing method on each of the LivDet database. The performance of texture features (BSIF, WLD, LPQ, LCPD, and Ric-LBP) is evaluated using three classifiers, i.e. SVM, KNN, Tree on standard LivDet databases (2011, 2013, 2015). Thereafter, the performance is evaluated using SVM classifier on Cross-dataset (LivDet 2011 and LivDet 2013) to check performance of a classifier when presented with test samples that are acquired from different sensors. For instance, in cross-dataset experiment, classifier is trained using Biometrika-2011 dataset and testing using Italdata-2013. Additionally, the performance of SVM classifier is investigated when fingerprint samples made of unknown spoof materials (not available in testing set) are presented during test set evaluations. The performance of classifier-fusion and feature-fusion are evaluated on LivDet 2015, and LivDet 2013 databases, respectively. At last, the performance of combine datasets (training set of all sensors and testing set of all sensors) is evaluated on LivDet 2011, 2013, and 2015 databases.

CONTRIBUTIONS

The major contributions that were made by me are as follows:

- Curvelet-based features, energy and co-occurrence features are extracted for LivDet 2013 and 2015 databases.
- Five different classifiers, i.e. Support Vector Machine (SVM), Decision tree, Random forest, Tree ensemble, and Probabilistic neural network (PNN) are used to evaluate the performance of energy and co-occurrence features.
- Performance is also evaluated on concatenation of energy and co-occurrence features, and energy and average of co-occurrence features.
- For LivDet 2015, texture features such as BSIF, LPQ, WLD, Ric-LBP, and LCPD are extracted and tested using SVM, KNN and Decision Tree on matlab.
- Evaluated the performance of single classifier (SVM) on cross dataset for LivDet 2011 and 2013 and on feature fusion for LivDet 2013.
- For LivDet 2015, training and testing data of all the sensors is combined and performance is evaluated using svm classifier.

I would like to appreciate my partner contribution in the project. His major contributions involve:

- For curvelet-based features, he has done the same part on LivDet 2009 and 2011.
- For LivDet 2011 and 2013, texture features such as BSIF, LPQ, WLD, Ric-LBP, and LCPD are extracted and tested using SVM, KNN and Decision Tree on matlab.
- Performance of single classifier (SVM) is evaluated on cross material for LivDet 2011 and 2013 and on classifier fusion using fusion techniques such as max, mean and majority voting rule for LivDet 2013.
- For LivDet 2011 and 2013, training and testing data of all the sensors for each year are combined and performance is evaluated using svm classifier.

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1. INTRODUCTION

1.1 Biometric Recognition:

A biometric recognition system is a type of pattern recognition system that uses biometric data such as fingerprint data, from an individual, extract different features from them, and compare those features against the biometric pattern present in the database. There are two ways a biometric system can operate based on application, i.e. identification mode and verification mode.

In case of verification mode, the biometric system checks and compares the captured biometric data such as fingerprint with biometric sample stored in the system database and verifies the identity of a person. In such a system, an individual must have a smart card, personal identification number (PIN) etc. to get verified. In this case, one-to-one comparison is conducted by system to determine whether the claim is real or not.

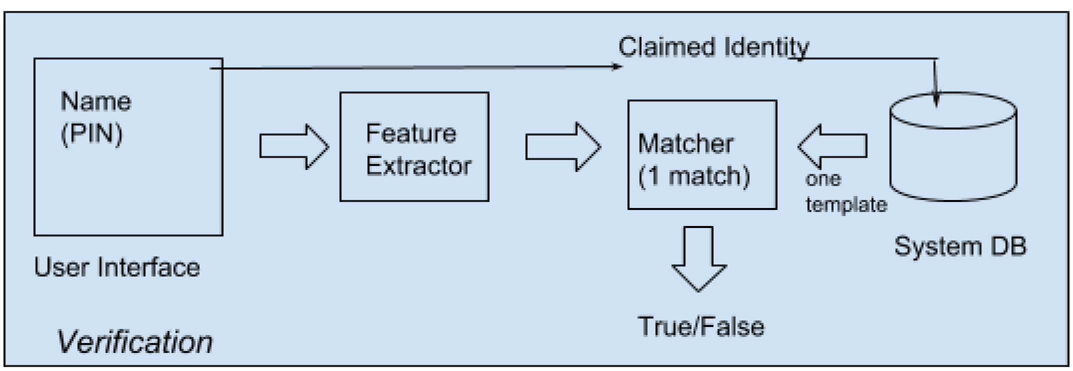

Fig. 1. Schematic diagram of the verification process showing four modules of the biometric system.

In the identification mode, the biometric system checks and compares the captured biometric data such as fingerprint with all biometric sample stored in the system database and verifies a person's identity. Therefore, one-to-many comparison is performed by the system for an individual verification. In this case, the subject does not need to claim an identity.

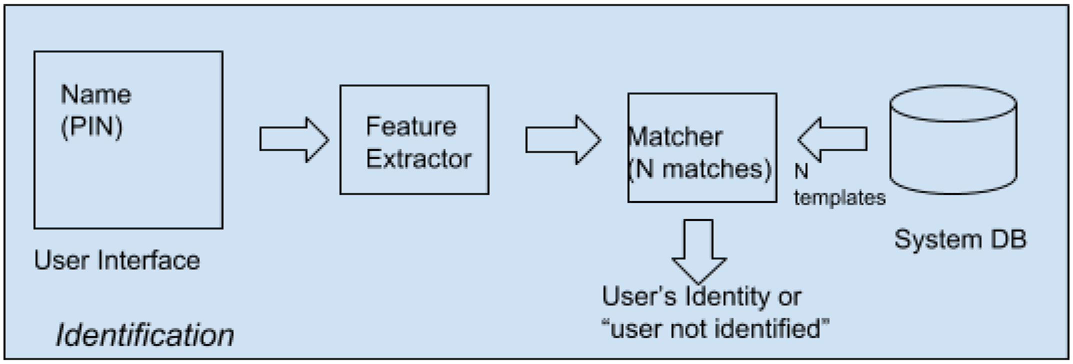

Fig. 2. Schematic diagram of the identification process showing four modules of biometric system.

These are the four important modules of a biometric system:

1. Sensor module: biometric data of an individual is captured using this module e.g. fingerprint sensor.
2. Feature extraction module: used for extracting distinctive features. For example, textural features such as curvelet energy, co-occurrence signatures, BSIF, LPQ, WLD etc of a fingerprint image are extracted in this module for a fingerprint-based biometric system.
3. Matcher module: in this module, the features in the stored database are compared against features extracted during recognition to generate matching scores.
4. System database module: this is used for storing the biometric templates of the enrolled users. New individuals are enrolled into the biometric system database using enrollment module.

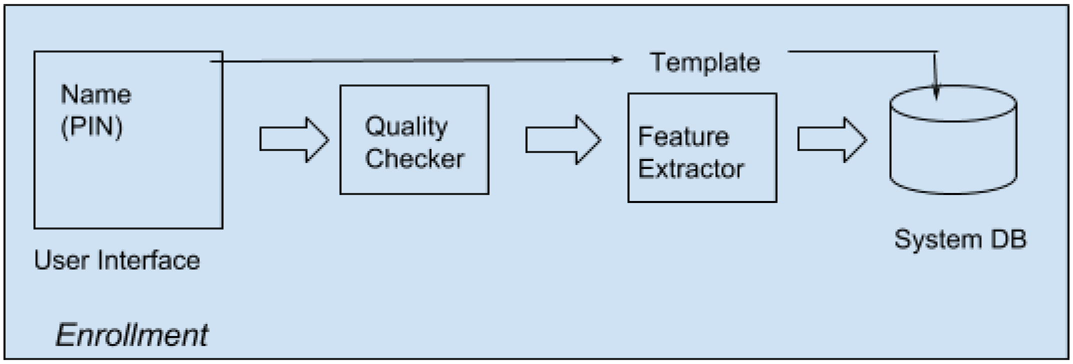

Fig. 3. Schematic diagram of the enrollment process showing four modules of the biometric system.

1.2 Fingerprint Recognition and Vulnerabilities:

Fingerprint recognition is a process of automatically verifying a match between two human fingerprints. Fingerprints are utilized in various domains such as forensic science, industries, and bank lockers etc. Fingerprints are used to identify an individual and verify their identity through software-based and hardware-based techniques. The skin of human fingertips form the distinctive patterns consists of ridges and valleys. Different research studies on fingerprint suggest that fingerprints are unique for each individual, i.e. no two persons have the same fingerprints. Because of this characteristic, fingerprints are very popular for biometrics applications.

However, recently it has been observed that by presenting fake fingers, fingerprint biometric systems can be deceived easily. A fingerprint can be replicated using spoofing material like silicone, clay, gelatin etc, and standard electronic sensors cannot distinguish between the real one and replica.

1.3 Fingerprint liveness detection:

To detect the liveness of fingerprint image i.e. if the image belongs to alive fingertip or to an artificial replica of it, fingerprint liveness detection system is used. A standard verification system can obtain additional information from the fingerprint data to detect the liveness degree of the given fingerprint. For this, software-based techniques uses image processing algorithms to capture textural information from the collected fingerprint image, while hardware-based systems uses extra sensors for measurements[2]. These systems are used for classification of images as either real or fake.

Real and fake fingerprint have different texture characteristics that can be used to detect liveness. Gray levels are non uniform along ridges in real fingerprint images due to skin quality (e.g. wet, dry, dirty skin, etc), perspiration phenomenon, sweat pores, skin elasticity, etc. Fake fingerprints are made of spoofing materials such as gelatin, silicone, clay, etc. For fake fingerprints, gray level are uniform along ridges because the material characteristics used for the fabrication of fake images do not change for surfaces. Also, textural characteristics of live and spoof fingerprint images are different such as: gray level pattern distribution, ridge widths and inter-ridge distances, presence of pores, ridge discontinuities, etc. So we use various texture features such as curvelet energy and GLCM, BSIF, LPQ, WLD, RicLBP, LCPD to capture these textural differences of real and fake images.

2. OBJECTIVES

This project aims to achieve the following objectives:

1. *To evaluate the performance of curvelet-based texture features using various classifiers* : This involved extracting various curvelet-based texture features such energy signature and co-occurrence signature using curvelet transform[2], and evaluated the performance of five different classifiers i.e., SVM, decision tree, random forest, tree ensemble, PNN, on four different combinations of feature vectors of curvelet-based features. We have used standard LivDet (2009, 2011, 2013 and 2015) as our datasets, and energy features, GLCM features, energy and GLCM features combined, energy and average of GLCM features as our four combinations of feature vectors to evaluate their performance.
2. *To evaluate the performance of texture features for fingerprint liveness detection system* : This involved extracting various texture features such as LPQ[6], WLD[7], BSIF[8], LCPD[9], RicLBP[10] from LivDet datasets of 2011, 2013, 2015 and using three classifiers such as SVM, KNN, Decision Tree on them to find out the best classifier which can distinct the fingerprints data with less error on those textural features.
3. *To evaluate the performance on standard LivDet(2011, 2013) for cross-dataset and cross-material scenario* : Using single classifier as SVM we evaluated the performance on eight different combination of two sensors i.e., Biometrika and Italdata taking one dataset as train and another as test dataset and find out average classification error by different textural features mentioned in our project, and compared the performance of them with textural features mentioned in literature. In case of cross-material[4], we trained and tested our datasets with different sensors to check the classifiers performance when it is tested and trained with different spoofing materials.
4. *To evaluate the performance using classifier fusion technique on LivDet 2015 and feature fusion technique on Livdet 2013* : We have fused three different classifiers using max

rule, mean rule, majority voting fusion techniques and evaluated their performance on LivDet 2015. Similarly, we also fused various combination of two different textural features among all the given textural features and reported its accuracy.

5. *To evaluate the performance on each LivDet(2011, 2013, 2015) by training all datasets at once* : We have combined all the training and testing data of all the sensors present in given LivDet separately[4], evaluated their performance and compares with average of performance given by each sensor for a given texture feature.

3. LITERATURE REVIEW

This project aims to classify, compare and evaluate the performance of the various combination of well-known textural features described in the literature. Therefore, we studied several texture-based techniques present in literature and evaluated their performance along with the different combination of their feature vectors in order to minimize classification error.

The software-based methods can discriminate live and fake fingerprints by analyzing the texture features extracted from fingerprint images. Nikam et al. [2] proposed a liveness detection method based on the texture analysis of the fingerprint images which extracts distinguishable features such as co-occurrence signature and energy signature through a texture measure method i.e., the curvelet transform.

Ville et al. [6] proposed a new method that works on Fourier phase called LPQ texture-based method. For every image position the fourier phase is computed locally for a window. Then, the quantization of the phases of four low-frequency coefficients is done uniformly into one of 256 hypercubes in 8-dimensional space, which results in 8-bit code. Then a histogram is formed using these LPQ codes for all image pixel neighbourhoods. This histogram represents the texture of an image and can be used for classification.

Gragnaniello et al. [7] also proposed a new descriptor for texture classification called WLD, based on the Weber's law which states that the difference between two stimuli is proportional to the magnitude of the stimuli. In high intensity region, the difference between values of surrounding pixel and central pixel are indistinguishable. Whereas in low intensity region, that same difference is more significant. And with respect to the central pixel's intensity, this difference is normalised. Two components of features are extracted: differential excitation and orientation. For differential excitation, 8 bins are extracted and for orientation 120 bins are extracted. And these finally constitute to 960 values histogram.

Juho et al. [8] proposed a method called BSIF, which is based on statistics of natural images. BSIF uses the histogram based representation of image regions by constructing local image descriptors that can efficiently encode texture information of an image. For each pixel binary codes are calculated by linearly projecting local image patches onto a subspace. Natural images are used for learning basis vectors via independent component analysis. Then, the coordinates in this basis are binarized using thresholding.

Gragnaniello et al.[9] proposed another descriptor called LCPD, which is based on two components: a spatial-domain component and and a phase component. Phase component is inspired by the rotation-invariant version of LPQ, and spatial-domain component is inspired by the homologous part of WLD. For extracting the information on the local amplitude contrast, and on the local behaviour of the image, the image is analysed both in the spatial and transform domain for each pixel, in parallel. These two features, collected over the whole image to form a 2D histogram. The rows of this 2D histogram are concatenated together to form a 1D histogram and used for classification.

Nosaka et al.[10] proposed a new type of LBP-based feature called RIC-LBP, that simultaneously has the characteristics of rotation invariance and high descriptive ability. Since CoALBP considers the global relation among LBPs, it has a higher descriptive ability as compared to the original LBP. By introducing rotation equivalence class to the CoALBP, the proposed method obtained rotation invariance.

4. DESCRIPTION OF TEXTURAL FEATURES

4.1 Curvelet based features

The proposed curvelet transform by Candes and Donoho[11] provides sparse representation by analysing the image that have edges along regular curves. And fingerprints are a pattern of only ridges oriented in various directions. Therefore, curvelets can easily process these patterns of fingerprint. In this paper, curvelet-based features are extracted using curvelet transform on standard LivDet datasets to detect liveness.

Curvelet transform is implemented in following four steps[2]:

1) **Subband decomposition**: An image f is divided into resolution layers called subbands. Each layer contains different frequencies.

2) **Smooth partitioning**: Each subband is smoothly partitioned into squares of an appropriate scale.

3) **Renormalization**: Renormalization to unit scale of each resulting square using a transport operator T_Q[11].

4) **Ridgelet analysis**: Discrete ridgelet transform is used for analysing each square.

In the implementation of digital curvelet transform, two parameters are involved: number of scales (resolutions) and number of angles at the coarsest level. An image is decomposed in S = 3 scales using real-valued curvelets.

The number of subbands at scale 2, 3, . . . , $N_{scales}-1$, is calculated by:

$$\boldsymbol{l}_j = \mathbf{16} \times 2^{Ceil((N_{scales} - i)/2)} ,$$

where $i=N_{scales}$, j=2; $i=N_{scales}$-1, j=3; . . . . ; i=3 and $j=N_{scales}$-1.

So, at level 1 i.e., finest level, we get 1 subband and at level 2(second coarsest level), we get 16 subbands and at last coarsest level, there is 1 subband. Thus, we obtain J=18 subbands. The calculation of curvelet energy and co-occurrence signatures from these 18 subbands are as follows.

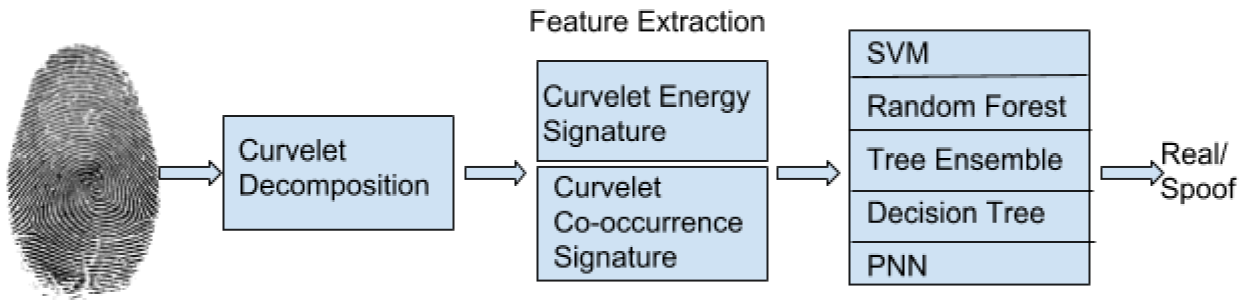

Fig. 2. Block diagram of curvelet based liveness detection method.

4.1.1 Curvelet energy signature

Energy is calculated using given formula [16]:

$$E_{B_n} = \frac{1}{M_n} \sum_{m=1}^{M_n} c^2_{n,m}$$

where E_{B_n} is normalized energy of subband B_n containing M_n coefficients, $c_{n,m}$ and n ($n = 1, 2, ..., J$) represents the subband number.

The feature vector (E_{B_1}, E_{B_2},...., E_{B_j}) contains energy of each subband.

We also use mean deviation MD_{B_n} of the subband B_n. It is given below[16] :

$$MD_{B_n} = \frac{1}{M_n} \sum_{m=1}^{M_n} |c_{n,m}|$$

For energy signature feature vector, both energy and mean deviation are concatenated. Now, the size becomes 36 (2 features from each of the 18 subbands) for this feature vector.

4.1.2 Curvelet co-occurrence signature

For each curvelet subband gray level cooccurrence matrix(GLCM) is computed. Second-order statistics like the probability of a particular spatial relationships, two pixels are having particular gray levels, describes the pixel gray level. The matrix element $P(i, j, d, \theta)$ represents the number of pixel pairs having the gray level i and j that are defined by specified distance d and direction θ. For each of the 18 subbands, we compute a GLCM. And, from each GLCM, we compute 9 texture features: entropy, inverse difference moment, contrast, angular second moment, maximum probability, homogeneity, correlation, cluster prominence and cluster shade. We then combine texture features obtained to get 162 (9 features from each 18 subbands) dimensional co-occurrence signature. Co-occurrence signatures are computed from various GLCMs for different combinations of d and θ, and test them on different classifiers, to choose best value for d and θ. And $d = 1$ and $\theta = 45^\circ$ gave the highest accuracy, hence we use $d = 1$ and $\theta = 45^\circ$ to compute GLCMs here.

4.2 Local phase quantization (LPQ)

Local Phase Quantization[6] uses short-term fourier transform(STFT) for analysing the image $f(.)$ in the Fourier domain:

$$F_x(u) = \sum_y f(y) w(y - x) e^{-j2\Pi u.y}$$

where x, y and u are two-dimensional coordinates in space and frequency (the latter), $w(.)$ is a suitably compact window that enforces locality of the transform, and $F_x(.)$ is the output STFT around x.

Then, four frequencies are considered, $u_0 = (a,\ 0)$, $u_{45} = (a,\ a)$, $u_{90} = (0,\ a)$, and $u_{-45} = (a,\ -a)$, with $a \ll 1$. The phase of $F_x(u)$ is computed for each of these frequencies and quantized with a 2-bit uniform quantizer to obtain an 8-bit feature vector $[q_1, \ldots, q_8]$. This can represented by an integer value in the range $[0 - 255]$: $LPQ = \sum_{i=1}^{8} q_i 2^{i-1}$. Finally, from all image positions, these integer values forms a histogram. This histogram is used as a 256-dimensional feature vector for classification

4.3 Weber local descriptor(WLD)

The WLD[7] uses two components of features: orientation and differential excitation. The orientation is given by:

$F_1(x) = \theta(x) = angle(\nabla I(x))$, where $\theta(x)$ is angle of local gradient.

And the differential excitation is given by :

$$F_2(x) = \xi(x) = \frac{\bar{I}_{3\times3}(x) - I(x)}{I(x)}$$

where $\bar{I}_{3\times3}(x)$ denotes the sample average of I over the 3×3-pixel square centered on x. The numerator is proportional to the difference between the average intensity of neighbor pixels ($\bar{I}_{3x3}(x)$) and intensity of target pixel($I(x)$). Therefore, in case of flat areas of image the feature is zero and grow larger where discontinuities exists.

The orientation is uniformly quantized in the range $[\pi, -\pi]$ with N_1 output levels. Then non-uniform quantization of differential excitation is performed, to consider the unbounded range induced by the ratio and the high-dynamics, using a uniform N_2-level quantizer in $[-\pi/2, \pi/2]$ after an *arctan* nonlinearity.

Then the outputs are joined together into a single integer which is given:

$$C(x) = WLD(x) = C_1(x)N_2 + C_2(x)$$

with values in $[0, N1N2 - 1]$. To get feature vector of length 960, typical values are $N1 = 8$ and $N2 = 120$.

4.4 Binarized statistical image features (BSIF)

Instead of manual tuning, BSIF[8] uses an approach consists of apply learning to obtain statistically relevant representation of the fingerprint data. Simple element-wise quantisation is used for efficient information encoding. The histograms of BSIF code values for each pixel are then calculated to characterise the texture properties within each fingerprint sub-region. Then, with a threshold at zero, the value of each element in the BSIF binary code string is calculated by binarising the response of a linear filter.

In short, given an image patch X of size $l \times l$ pixels and a linear filter W_i of the same size, the filter response s_i is obtained by

$s_i = \sum_{u,v} W_i(u, v)X(u, v) = w_i^T x$, where vector w and x contain the pixels of W_i and X.

The binarised feature b_i is obtained by setting $b_i = 1$ if $s_i > 0$ and $b_i = 0$ otherwise.

4.5 Local contrast phase descriptor(LCPD)

The basic idea of WLD is further developed in LCPD with some important improvements[9]. Again, two features describing roughly orientation and contrast are defined and analyzed jointly. However, a different measure of contrast and the angle of the gradient which is replaced by the rotation invariant version of the LPQ feature is used, defined as

$$F_2(x) = \xi(x) = \frac{LoG[I(x)]}{I(x)}$$

For the highly descriptive LPQ feature 256 bins are reserved contrary to WLD, and only a dozen or so for the contrast. This is obtained by uniform quantization with N_2 levels after passing the feature through the arctan non-linearity. When N2 = 8, the final feature becomes relatively long, i.e., 2048, and if the training set is relatively small, might results in overfitting problems. So, a feature reduction technique is used for single bins out the more descriptive bins of the histogram.

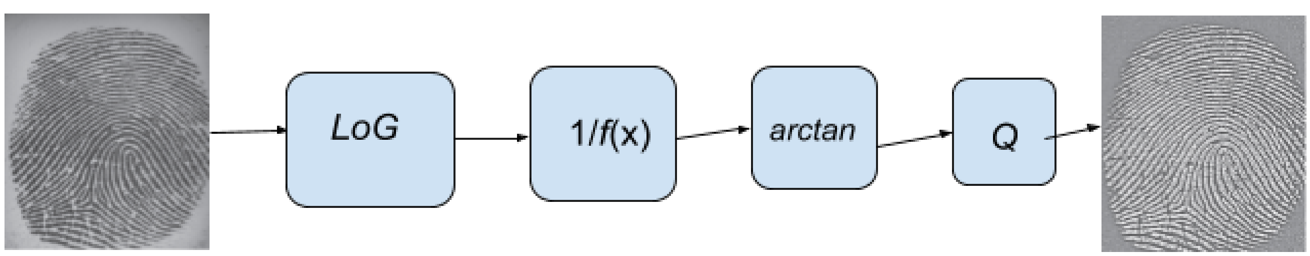

Fig. 3. Schematic diagram for the computation of the local contrast phase descriptor.

4.6 Rotation Invariant Co-occurrence among Adjacent LBPs(RicLBP)

To exploit richer and longer-range dependencies, multi-resolution LBP uses the larger neighborhoods. But the problem arises when including more features, increases the length of the feature vector which grows rapidly[10].

A simple solution to this is use Co-occurrence of Adjacent LBPs (CoA-LBP) [12]. The name is self-explaining: the Kth bi-dimensional histograms h_k are calculated after extracting C, with

$$h_k(i, j) = \sum_x \delta(C(x) - i, C(x + \Delta_k) - j)$$

These histograms are concatenated after vectorization to obtain the final feature **h**. The co-occurrences of couples of LBP's separated spatially by the vector Δ_k are then described by k-th bi-dimensional, thereby manipulating dependencies at a somewhat extended range. With these LBP's, four such histograms are calculated by taking at distance $\|\Delta_k\| = 3$ along directions 0°, 45°, 90°, and 135°. Then, P = 4 is considered for the basic LBP to reduce the feature length, so, we eventually obtain features of length 1024 (without considering symmetries). Couples of LBP's corresponding to rotated configurations are merged together in Ric-LBP for obtaining some reduction in feature length.

5. EXPERIMENTAL RESULTS

This chapter discusses the experimental setup used for the experiments and the implementation details of the proposed algorithms. Section 5.1, specifies the parameter values of different classifiers used and details of proposed algorithms. Section 5.2, gives description of the databases used. Section 5.3, gives performance details of curvelet based texture features (energy and GLCM). Section 5.4 gives details about other texture features like BSIF,LCPD etc.

5.1 Classifier and Algorithms

For curvelet based features, five classifiers such as SVM(Support Vector Machine), Random Forest, Tree ensemble, Decision tree, and PNN (Probabilistic neural network) on KNIME are used. For SVM kernel used is radial basis function(rbf) with sigma value 0.1. Random forest used random seed and gini index as split criterion. Tree ensemble and PNN were set to default values. Decision tree used gini index as quality measure and MDL as pruning method.

For other texture features like BSIF, LPQ etc. three classifiers such as SVM, Tree and KNN on matlab are used. SVM(fitcsvm on matlab) used Iterative Single Data Algorithm(ISDA) solver and linear Kernel Function. For Tree(fitctree in matlab) pruning by finding the optimal pruning level using cross validation is used. For knn number of neighbors used are 10.

Table I gives details of various algorithms implementation.

Descriptor	Size	Implementation	Software code
Curvelet Energy	36	Matlab	http://www.curvelet.org/software.html
Curvlet GLCM	162	Matlab	http://www.curvelet.org/software.html
BSIF	4096	Matlab	http://www.ee.oulu.fi/~jkannala/bsif/bsif.html
LCPD	2304	Matlab	http://www.grip.unina.it

LPQ	256	Matlab	http://www.cse.oulu.fi
RicLBP	408	Matlab	http://www.cvlab.cs.tsukuba.ac.jp/ nosaka
WLD	960	Matlab	http://www.cse.oulu.fi

All the result are in terms of Average Classification Error (ACE) which is the average of fake positive rates and fake negative rates i.e. The average of the rate of misclassified live examples and the rate of misclassified fake examples.

5.2 Databases

Liveness Detection(LivDet) Competitions held in the years of 2009[13], 2011[14], 2013[15], and 2015[16] provides the fingerprint and iris datasets. In this study, we have used fingerprint dataset for experimentation.

LivDet 2009 consists of almost 18,000 images of fake and real fingerprints. Three different sensors such as Crossmatch, Biometrika, and Identix are used. Gelatin, Play Doh, and Silicone are used for fabrication of fake fingerprints. Two third of images are used for testing and remaining for training for each dataset.

LivDet 2011 consists of 16,056 images of fake and real fingerprints. Four different sensors such as Digital, Biometrika, Sagem, and Italdata are used. Each sensors has 2000 images of fake and real fingerprints. For training and testing data, dataset is divided into two equal halves. Four different materials such as Gelatin, Silgum, Wood Glue, and Eco Flex are used for fabrication of fake fingerprints.

LivDet 2013 consists of 16,852 images of real and fake fingerprints. Four different sensors such as Crossmatch, Biometrika, Swipe, and Italdata are used. Each sensor consists of approximately 2,000 images of fake and real fingerprints. For training and testing data, dataset is divided into two equal halves. Here, five different materials such as Gelatin, Eco Flex, Latex, Modasil, and Wood Glue are used for fake image fabrication.

For 2013 dataset we are not using the Crossmatch dataset, because due to an acquisition problem, it can't be used for checking the performance of liveness detection algorithm.

LivDet 2015 consists of 19,423 images of fake and real fingerprints. Four different sensors such as Biometrika, Green Bit, Crossmatch, and Digital Persona are used in this database. Each sensor has 2,500 images of real and fake fingerprints. For training and testing data, dataset is divided into two equal halves. Here, Six different materials(except for Crossmatch) such as Latex, Ecoflex, Liquid Ecoflex, Gelatine, WoodGlue, and RTV are used for fake image fabrication. For Crossmatch, material used are: Playdoh, Body Double, Gelatin, Ecoflex, and OOMOO.

5.3 Classification Results for Curvelet based features

Curvelet energy signatures and co-occurrence signatures are tested independently on five different classifiers SVM, Decision Tree, Random Forest, Tree Ensemble, PNN using KNIME Data Analytics Software.

First fingerprint data are classified separately based on co-occurrence features and energy features. For co-occurrence features, average of same feature calculated from GLCM of all 18 subbands is also taken. This result in 9 columns each representing the average of same feature from 18 subbands.

Finally, co-occurrence and energy signatures are combined to get a fused signature and tested on different classifiers because it gives better performance compared to others. First combination contains 36 features of energy and 162 features of GLCM (9 features for each of 18 subbands) and second combination contains 36 features of energy and average of 18 subbands for each of 9 features.

	Energy		GLCM		Energy and GLCM Combined (36+162)		Energy and GLCM Combined (36+9)	
Sensor	ACE	Classifier	ACE	Classifier	ACE	Classifier	ACE	Classifier
Biometrika	11.51	Tree Ensemble	15.85	Random Forest	**9.99**	Tree Ensemble	10.70	Random Forest
Cross -match	15.13	Random Forest	24.78	Random Forest	**11.90**	Tree Ensemble	13.20	Tree Ensemble
Identix	11.87	Random Forest	22.38	Random Forest	9.78	Tree Ensemble	**7.98**	Random Forest

Table II. Average Classification Error on LivDet 2009 database for curvelet features. Highest accuracy classifier for each sensor is reported..

	Energy		GLCM		Energy and GLCM Combined (36+162)		Energy and GLCM Combined (36+9)	
Sensor	ACE	Classifier	ACE	Classifier	ACE	Classifier	ACE	Classifier
Biometrik a	33.20	Random Forest	31.70	Random Forest	24.75	Random Forest	**24.05**	Tree Ensemble
Digital	26.35	Tree Ensemble	26.05	Random Forest	**21.70**	Tree Ensemble	25.90	Tree Ensemble
Italdata	32.45	Tree Ensemble	39.40	Tree Ensemble	33.30	Random Forest	**28.70**	Tree Ensemble
Sagem	21.02	Tree Ensemble	28.29	Random Forest	22.45	Tree Ensemble	**21.53**	Tree Ensemble

Table III. Average Classification Error on LivDet 2011 database for curvelet features. Highest accuracy classifier for each sensor is reported.

	Energy		GLCM		Energy and GLCM Combined (36+162)		Energy and GLCM Combined (36+9)	
Sensor	ACE	Classifier	ACE	Classifier	ACE	Classifier	ACE	Classifier
Biometrika	11.85	Random Forest	6.15	SVM	7.65	Random Forest	**6.70**	Random Forest
Crossmatch	29.02	Random Forest	24.80	Random Forest	25.29	Random Forest	**17.96**	Random Forest
Italdata	20.10	Random Forest	8.35	Random Forest	**6.55**	Tree Ensemble	11.50	Random Forest
Swipe data	23.73	Tree Ensemble	19.18	Tree Ensemble	**19.37**	Random Forest	25.50	Tree Ensemble

Table IV. Average Classification Error on LivDet 2013 database for curvelet features. Highest accuracy classifier for each sensor is reported.

	Energy		GLCM		Energy and GLCM Combined (36+162)		Energy and GLCM Combined (36+9)	
Sensor	ACE	Classifier	ACE	Classifier	ACE	Classifier	ACE	Classifier
Crossmatch	12.62	Tree Ensemble	30.56	Random Forest	12.99	PNN	**12.96**	Tree Ensemble
Digital_Persona	30.28	Tree Ensemble	34.96	Tree Ensemble	**28.24**	Tree Ensemble	28.80	Random Forest
Green Bit	23.05	Tree Ensemble	20.96	Tree Ensemble	**19.36**	Tree Ensemble	23.25	Random Forest
Hi Scan	26.44	Tree Ensemble	20.36	Tree Ensemble	**17.72**	Tree Ensemble	22.84	Tree Ensemble

Table V. Average Classification Error on LivDet 2015 database for curvelet features. Highest accuracy classifier for each sensor is reported.

5.4 Classification Results for texture features(LPQ, WLD, BSIF, LCPD, RicLBP)

LivDet 2011, 2013 and 2015 databases are used for feature extraction using BSIF, LCPD, LPQ, RicLBP and WLD texture feature. First the performance of each feature is evaluated separately using 3 classifiers i.e. SVM, Tree and KNN and minimum error rate among all three classifiers is reported in Table VI, VII and VIII.

Sensor \ Features	BSIF	LCPD	LPQ	RicLBP	WLD
Biometrika	8.05	**4.80**	13.45	17.55	12.6
Digital	**3.25**	5.25	8.50	10.20	16.95
Italdata	14.30	**11.30**	20.05	29.15	28.20
Sagem	5.60	**3.44**	12.13	11.59	9.92

Table VI. Average Classification Error using different texture features on 2011 database.

Sensor \ Features	BSIF	LCPD	LPQ	RicLBP	WLD
Biometrika	1.50	**1.15**	2.80	6.45	8.80
Italdata	**0.75**	3.3	2.30	13.60	9.55
Swipe	**4.27**	15.00	26.38	21.41	12.82

Table VII. Average Classification Error using different texture features on 2013 database.

Sensor \ Features	BSIF	LCPD	LPQ	RicLBP	WLD
Cross Match	6.65	17.10	5.02	**0.10**	9.63
Digital Persona	13.72	14.6	**12.60**	17.24	21.20
Green Bit	7.86	**2.04**	20.52	9.70	14.63
HiScan	9.00	**6.68**	15.72	11.20	19.52

Table VIII.Average Classification Error using different texture features on 2015 database.

The performance of classifier fusion with fusion schemes(max, mean, majority voting rule) using svm, tree and knn on LivDet 2015 database is evaluated.

Sensor \ Features	BSIF	LCPD	LPQ	RicLBP	WLD
Cross Match	5.97	50.88	4.92	**0.10**	11.40
Digital Persona	15.96	56.04	**14.44**	18.04	20.12
Green Bit	7.82	**3.85**	39.88	10.46	12.71
HiScan	9.68	**8.00**	17.64	10.28	18.04

Table IX. Average Classification Error of classifier fusion on LivDet 2015 database.

Then, using feature fusion techniques, each of these 5 features are fused with other 4 features and evaluates the performance. Table X shows minimum error rates for different sensors.

(Feature1,Feature2) \ Sensor		Biometrika	ItalData	SwipeData
BSIF	LCPD	1.15	6.85	13.934
	LPQ	1.3	**0.65**	5.57
	RICLBP	1.5	1.1	**4.41**
	WLD	1.55	0.75	4.88
LCPD	LPQ	1.05	3.3	25.82
	RICLBP	1.45	3.3	15.00
	WLD	**1**	3.45	14.86
LPQ	RICLBP	2.1	2.3	25.04
	WLD	**1**	1.65	18.44
RICLBP	WLD	4.45	6.25	13.24

Table X. Average Classification Error of Feature Fusion on 2013 database.

On Livdet 2011 and 2013 databases, performance is evaluated on cross dataset and cross material and compared it with the paper in literature[4].

Train Dataset	Test Dataset	CNN-VGG[4]	LBP[4]	BSIF	LCPD	LPQ	RicLBP	WLD
Biometrika 2011	Biometrika 2013	15.5	16.5	**14.4**	16.35	21.85	34.35	19.3
Biometrika 2013	Biometrika 2011	46.8	47.9	48.45	45.55	49	49.2	**34.5**
Italdata 2011	Italdata 2013	14.6	**10.6**	11.1	48.55	50.75	26.9	21.25
Italdata 2013	Italdata 2011	46.0	50.0	49.65	48.8	49.5	**42**	46.05
Biometrika 2011	Italdata 2011	**37.2**	47.1	37.9	42.4	50	50	50
Italdata 2011	Biometrika 2011	31.0	49.4	47.6	**24.35**	50	60	45.1
Biometrika 2013	Italdata 2013	**8.8**	43.7	50	49.75	49.6	50	50
Italdata 2013	Biometrika 2013	**2.3**	48.4	11.2	5.25	23.8	45.8	63.85

Table XI. Average Classification Error of Cross dataset evaluations on LivDet 2011 and 2013 databases.

Dataset	Material - Train	Material - Test	CNN-VGG [4]	LBP[4]	BSIF	LCPD	LPQ	RicLBP	WLD
Biometrika 2011	Ecoflex, Gelatin, Latex	Silgum, Woodglue	**10.10**	17.70	13.21	11.14	20.29	20.07	20.07
Biometrika 2013	Modasil, Woodglue	Ecoflex, Gelatin, Latex	4.90	8.50	**1.81**	3.25	3.13	7.50	11.81
ItalData 2011	Ecoflex, Gelatin, Latex	Silgum, Woodglue	22.10	30.90	17.93	**12.50**	20.14	26.07	30.50
ItalData 2013	Modasil, Woodglue	Ecoflex, Gelatin, Latex	6.30	10.70	3.44	4.56	**3.00**	17.5	10.06

Table XII. Average Classification Error of cross materials evaluations on LivDet 2011 and 2013 databases.

At last, for LivDet 2011, 2013, 2015 databases performance is evaluated on combination of all sensors for training with a single classifier (svm) and compared it with the average of ACE's from all the sensors.

LivDet 2011	BSIF	LCPD	LPQ	RicLBP	WLD
One Classifier trained using all training dataset	**10.71**	**8.30**	**11.71**	**15.03**	**15.49**
One Classifier per dataset	13.41	9.84	14.54	16.60	16.34

Table XIII. Average Classification Error when combining all sensors of LivDet 2011 database.

LivDet 2013	BSIF	LCPD	LPQ	RicLBP	WLD
One Classifier trained using all training dataset	5.01	**25.42**	17.50	14.68	11.10
One Classifier per dataset	**3.88**	29.25	**13.04**	**12.51**	**8.12**

Table XIV. Average Classification Error when combining all sensors of LivDet 2013 database.

LivDet 2015	BSIF	LCPD	LPQ	RicLBP	WLD
One Classifier trained using all training dataset	**10.04**	36.46	**17.16**	10.06	18.62
One Classifier per dataset	10.42	**25.72**	18.24	**9.72**	**16.67**

Table XV. Average Classification Error when combining all sensors of LivDet 2015 database.

6. CONCLUSIONS

This project work includes a study of various texture descriptors (i.e., Curvelet, BSIF, LCPD, LPQ, RicLBP, WLD) for fingerprint liveness detection. In curvelet-based feature extraction method, random forest and tree ensemble gives better accuracy than other classifiers and combination of energy and GLCM features, and energy and average of GLCM features gives better accuracy than both individual feature. In case of texture features other than curvelet-based features such as BSIF, WLD, etc, BSIF and LCPD can classify fingerprint images more accurately than other three features. Four out of eight cases gives better accuracy than the features given in the paper[4] in case of cross-dataset(LivDet 2011, LivDet 2013). When different types of sensors are used for testing and training, the error rates are high (>20%) in 5 out of 8 in case of BSIF and 6 out of 8 in case of LCPD which implies that the models fail to generalize. Three out of four cases gives better accuracy than the features given in the paper[4] in case of cross-material(LivDet 2011, LivDet 2013). The average classification error are lower in case of cross-material than Cross-dataset experiments, which implies that most of the generalization error came from different sensors but not from different materials. In case of combined training data and testing data of all sensors for a given LivDet dataset(2011, 2013, 2015), the results show that a single classifier trained with all datasets gives comparable error rates with individual classifiers trained per dataset. This suggest that if all datasets are trained together, the effort to design a liveness detection system can be considerably reduced. In case of feature fusion, error rates are better than at least one of the individual feature and for classifier fusion, error rates are better for some datasets (sensors) than all three classifiers individually.

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