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FINGERPRINT SPOOFING DETECTION USING LOCAL BINARY PATTERN AND HOG

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Abstract - Nowadays for biometric authentication system are used for security applications like verification and identification. Fingerprint, face and iris are the various biometric traits. Since the biometric traits are unique in nature, it is possible to avoid problems like password stolen or forgotten. Biometric has the capability to distinguish between real and fake. In this for software based fingerprint liveness detection we use Local Binary Pattern (LBP) for texture classification and Histogram of Oriented Gradient (HOG) for object detection and uses Support Vector Machine (SVM) classifies for classification. Through classification it is possible to distinguish between real and fake.

Index Terms— Fingerprint liveness detection, local binary pattern, Histogram of oriented gradients (HOG), Support Vector Machine (SVM)

I.INTRODUCTION

Biometric system has obtained an extensive range of applications in various security fields. Traditional identifiers are replaced by biometric identifiers since it is difficult to steal, replace, and forget a transfer. Over classical security methods biometric technology have several advantages based on either some information like PIN, password etc. or physical devices like key or cad etc. It is possible to spoof different fingerprint technologies by means of relatively in expensive or crude way. Through liveness detection it is possible to identify whether the biometric is coming from a live source. Even though fingerprint can be spoofed by various techniques like fake fingers made of gelatin (gummy fingers), clay, wax, Play-Doh, moldable plastic and silicon developed from, casts of fingers etc.

Figure 1 : Making an artificial fingerprint directly from a live finger plastic is used to obtain the mold and gelatin to obtain the cast.

In parallel high level image descriptions and global descriptions, local descriptions are recently used [1][2] where the local descriptors describes the statistical behavior of the observed small patches in the image by means of histogram. And through conventional classification tools, these histograms are used to classify the image.

A usual biometric system contains sensing, feature extraction and matching modules where the biometric techniques are classified into two classes.

1) Physiological based techniques: It consists of facial analysis, fingerprint, hand geometry, iris, DNA and it measures the physiological characteristics of a person.
2) Behavior based technique: It contains smell, voice, signature, sweat pore analysis and measure of behavioral characteristics.

For fingerprint liveness detection different algorithm have been proposed [3][4][5]. And it is broadly classified into hardware and software. In the hardware approach a specific device is included to the sensor to detect the properties like blood pressure [6] skin distortion [7] or the odor [8]. For software approach used in this work, fake traits are detected once the sample has been obtained with the standard sensor.

Figure2: Typical examples f real and fake fingerprint images that can be obtained from the LiveDet2009 database used in the experiments .Figure extracted from [9]

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II. RELATED WORK

A lot of fake attempts are detected in various authentication field. Different liveness detection algorithms have been proposed for various traits such as fingerprint, face and iris

One of the first efforts in fingerprint liveness detection was carried out by [10] who initiated a research line using the skin perspiration pattern. In this they considered the periodicity of sweat and the sweat diffusion pattern using a ridge signal algorithm. In a subsequent work [11], they used a wavelet based algorithm that improves the performance reached in their initial study and in further step [12] they extended both the works with new intensity that is based on perspiration liveness detection technique which had lead to detection rates around 90%.

And different fingerprint distortion models have been described in the literature[13,14], which led to the development of liveness detection technique based on flexibility properties of the skin[15,16]

In some works use general feature extractors such as Weber local descriptor (WLD) [17], which is composed on orientation components of differential excitation in [18] two general feature extractors are composed: Convolutional Neural Network (CNN) with random weights [19] and Local Binary Pattern(LBP) whose multiscale variant in [20] achieves a good result

In some research in parallel with the skin elasticity, a liveness detection procedure which is based on the corporal order [21] use a chemical sensor to discriminate the skin odour from the materials such as gelatin or silicon

Other liveness detection for fake fingerprint detection includes the analysis of perspiration and elasticity related features in fingerprint image sequences [22], using wavelets for the analysis of the finger tip surface texture [23], and a analyzing the tiny pattern of the Fourier spectrum [24]

In some sophisticated techniques which use texture descriptors as feature vectors, such as load phase quantization [25], LBP with wavelets [26] and BSIF [27] use the original and uniform LBP coding schemes

Outside the research field some companies proposed various methods for fingerprint liveness detection such as ultrasound [28, 29] on electrical measurements or light measurements.

III. PROPOSED METHOD

In the proposed system liveness detection method for fingerprint is tested using some databases.

A. Texture Analysis

In image analysis, texture is defined as a function of the spatial variation in intensities of pixels, where the texture analysis is commonly opted t discriminate between live and fake images. The grey level associated with fingerprint pixels can be used t analyze liveness, because the grey level distribution can change with the changes in the physical structure. The texture features are classified into first order statistics and second order statistics. The grey level distribution of a single pixels is referred to as first order statistics and the grey level distribution between pair of pixels is second order statistics which is incorporated using Haralick's textural features.

B. First Order Statistical Features:-

These feature can directly refer the observed difference in the 'live' and 'fake' fingerprint. And this is confirmed by changes in the type of histogram of various fingerprint .The basic difference is that first order statistics estimate properties of individual pixel values ignoring the spatial interaction between image pixels .If H(n) denotes the normalized histogram then the first order features used for this work are:-

$$\text{Skewness :- } \gamma 1 = \frac{1}{\sigma 3} \sum_{n=0}^{N-1} (n-\mu)^3 H(n)$$

$$\text{Kurtosis :- } \gamma 2 = \frac{1}{\sigma 4} \sum_{n=0}^{N-1} (n-\mu)^4 H(n)$$

$$\text{Entropy :- } S = -\sum_{n=0}^{N-1} H(n) \log H(n)$$

$$\text{Coefficient of variation} = Cv = \frac{\sigma}{\mu}$$

$$\text{Variance :- } \sigma^2 \sum_{n=0}^{N} (n-\mu)^2 H(n)$$

where N is the number of bins.

C. Second Order Statistical Features

For the calculation of second order statistical features , co-occurrence matrix is calculated .Grey level co-occurrence matrix (GLCM) is well-known statistical technique for feature extraction.

The main goal of the GLCM is to assign an unknown sample image to one of a set of known texture class. GLCM proposed by Haralick has become one of the most well known and widely used texture measures. Haralick features describe the correlation in intensity of pixels that are next to each other in space. The grey level co-occurrence matrix is the two dimensional matrix of joint probabilities P(i,j) between pairs of pixels separated by a distance 'd' in a given direction 'r'. The second order statistics estimate the properties of two or more pixel values occurring at specific location relative to each other.

Based on the definition of the co-occurrence matrix, following second order statistical features are calculated;-

$$\text{Contrast} = \sum_{i=1}^{m} \sum_{j=1}^{n} (i-j)\, 2\text{GLCM}(i,j)$$

$$\text{Homogeneity} = \sum_{i=1}^{m} \sum_{j=1}^{n} \frac{GLCM(i,j)}{1+|i-j|}$$

$$\text{Correlation} = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} \{i \times j\} \times GLCM(i,j) - \{\mu x \times \mu y\}}{\sigma x \times \sigma y}$$

$$\text{Energy} = \sum_{i=1}^{m} \sum_{j=1}^{n} (GLCM(i,j))^2$$

D. Feature Extraction

Local Binary Pattern:- LBP are the local texture descriptor that have performed well in computer vision applications which includes texture classification and segmentation, image retrieval etc.

In its original version, the LBP assigns a label to every pixel of an image by thersholding each 8 neighbors of the 3×3 neighborhood with the center pixel value and considers the result as a unique 8 bit code represents the 256 possible neighborhood combinations.

Let X be the generic pixel and $\eta i(X)$ the i^{th} of P neighbor which is sampled uniformly on a circle of radius R centered on X. The basic features used in LBP are simply directional differences.

$$F_i(X) = I(X) - I(\eta_i(X))$$

These features are quantized independently with a fixed two-level symmetric quantizer obtaining the indexes. A string of bits is represented synthetically by the integer.

$$C(X) = \sum_{i=0}^{P-1} Ci(X) 2^i$$

In the basic version f LBP these quantities are on subjected to further processing ,which leads to feature vector length 2^P , h= hist (C) where

$$h(i) = \sum_X \delta(C(X) - i)$$

When LBP is combined with Histogram of Oriented Gradient descriptor, it improves the detection performance considerably on some datasets. HOG is one of the well known features for object recognition.HOG features are calculated by taking orientation histograms of edge intensity in a local region.

The implementation HOG descriptors can be obtained by dividing the image into small connected regions called cells and for each cell compiling a histogram of gradient directions or edge orientations for the pixels within the cell.

SVM classifier is used to processing such classifier can be used for face recognition or texture analysis. A special property of SVM is that it can minimize the empirical classification error and maximize the empirical margin. So SVM called Maximum Margin Classifier.SVM maps the input vector to a higher dimensional space where a maximal separating hyper plane is constructed. Two parallel hyper plane are constructed on each side of the hyper plane that separate the data. The separating hyper plane is the hyper plane that maximize the distance between the two parallel hyper planes.

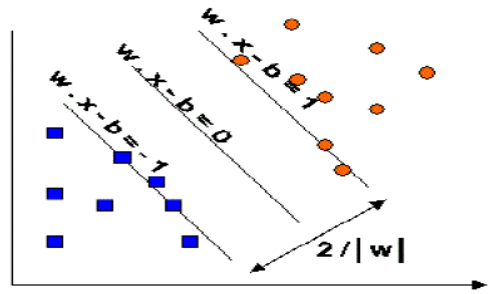

Figure 3: Maximum margin hyper plane for a SVM trained with samples from two classes.

IV. SYSTEM MODEL

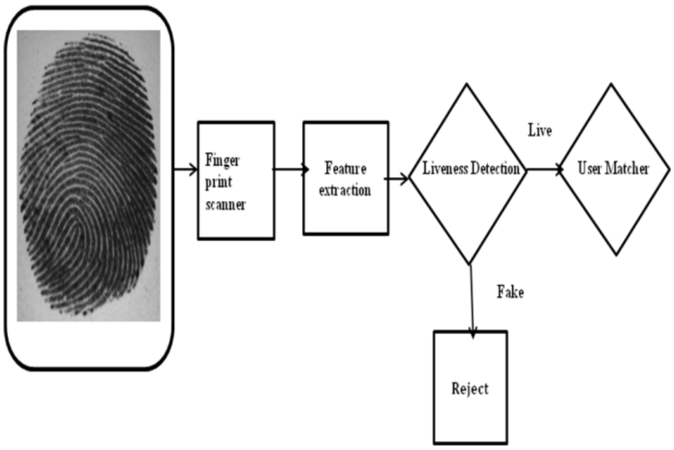

Figure 4: Block diagram of the system

V.SIMULATION RESULTS

Simulation procedure is carried in the MATLAB domain. The test images used throughout procedure were selected from the publically available data sets in this field. The images are shown below.

Figure 4: A

Figure 5: B

Figure 6: C

Figure 7: D

Figure 8: E

Figure 9: F

Figure 10: G

Figure 11: H

Figure 12: I

Figure 13:J

Figure 14: K

In this data set, the images A,B,C,D,E are spoof images and images F,G,H,I,J,K are real images. In order to check whether the images are spoof or real, computations are made to calculate features such as skewness, Kurtosis, Variance, Coefficient of variation, Entropy, Contrast, homogeneity, Energy, Correlation. Results are examined and recorded in a tabular column in table 1.

PAIRS	H&B		J&E		K&D	
Features	H	B	J	E	K	D
Skewness	- 0.033	-0.87	-0.30	-0.69	-0.22	-0.543
Kurtosis	1.6801	2.623	1.955	2.036	1.6892	0.0156
Variance	0.0317	0.028	0.026	0.048	0.033	0.056
Coefficient of variation	2.3940	3.064	3.023	1.924	2.433	4.423
Entropy	7.2916	7.073	7.021	7.17	7.285	7.163
Contrast	0.2468	0.421	0.468	0.368	0.776	0.542
Homogeneity	0.435	0.836	0.822	0.623	0.562	0.328
Energy	0.104	0.732	0.115	0.822	0.123	0.934
Correlation	0.746	0.901	0.865	0.523	0.9819	0.643

Table 1: Features obtained.

The image pairs H&B , J&E, K&D are pairs of spoof and real images where H,J,K are real and B,E,D are spoof images respectively. By examining the features of both spoof and real, we can distinguish them. MATLAB analysis shows pictorial representation of spoof detection.

A.ANALYSIS OF REAL IMAGE

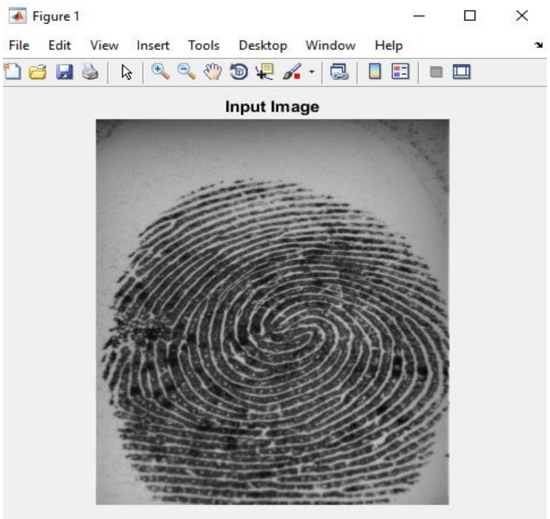

Figure 15: Input image

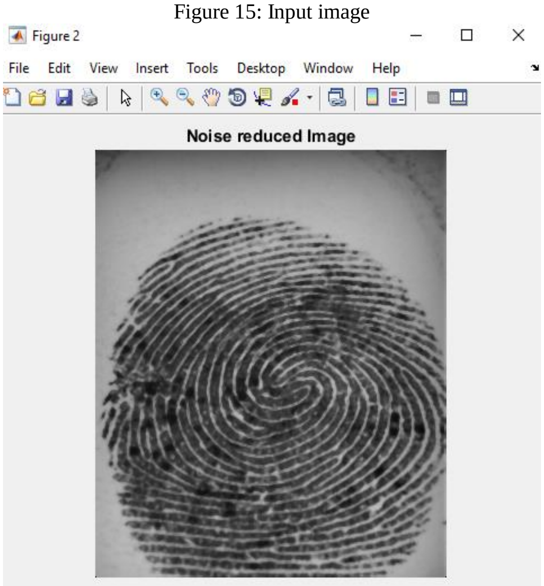

Figure 16: Noise reduced image

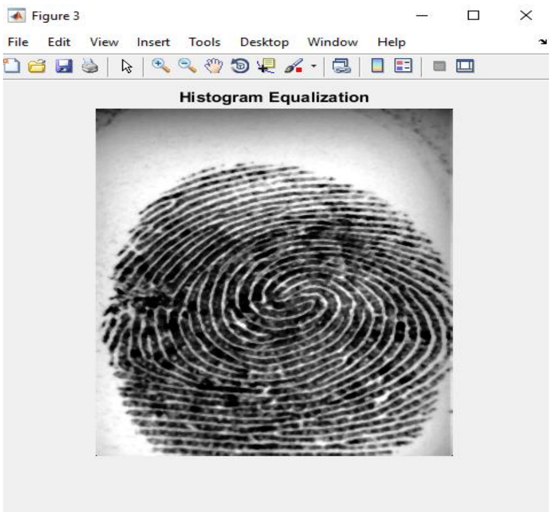

Figure 17: Histogram Equalization

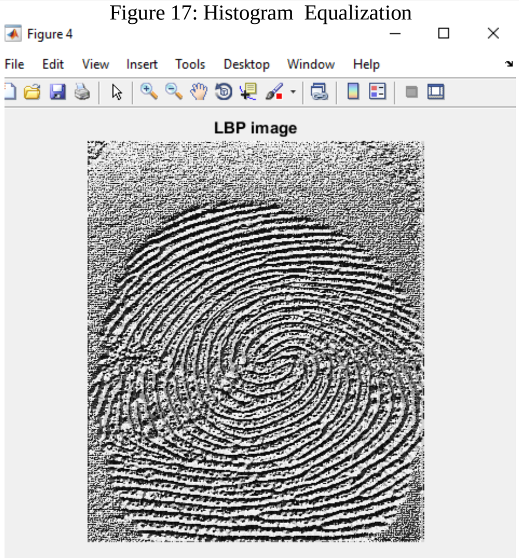

Figure 18: LBP image

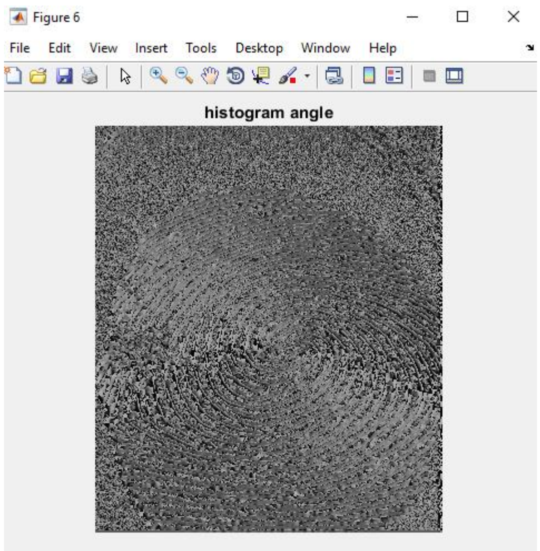

Figure 19: Histogram angle

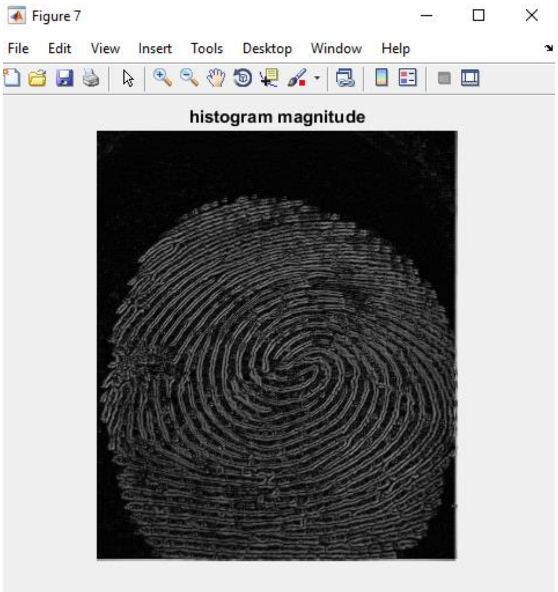

Figure 20: Histogram magnitude

VI CONCLUSION

From the analysis we can identify the real and spoof images by perfroming Local Binary Pattern and Histgram f riented Gradient.In this wrk analytical and stimulation of the images are done. Conventional methods for detection of liveness in a fingerprint image of a user included: Temperature detection, measurement of pulse, incorporation of the concept of pulse oximetry, electrocardiogram and detection of perspiration. Since the aforementioned methods turned out to be expensive, software methods are much preferred . The work is carried out in MATLAB domain which reduces hardware complexity and cost.

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