A Survey on Various Feature Selection Methods for Fingerprint Liveness Detection Techniques

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Abstract: *Use of biometric authentication system is growing in the recent years. Therefore, spoof fingerprint detection is also become important. In this survey, three techniques of feature extraction for fingerprint liveness detection is evaluated, such as Convolutional Neural Networks (CNN), Local Binary Patterns (LBP), and Fingerprint Pore Characteristics. In this, CNN and LBP are used in software – based techniques and Fingerprint Pore Characteristics is used in hardware – based technique. These systems are evaluated on the datasets obtained in the liveness detection competition of the year 2009, 2011, and 2013, having almost 50,000 real and fake fingerprints. Evaluation shows that we can achieve good accuracy on small training sets using pre –trained networks.*

Keywords: CNN, Fingerprint Pore Characteristics, LBP

1. Introduction

In the information era automatic access of people to services become important. As a result new technological area has established know as biometric recognition or biometrics [9].

The main aim of biometrics is to discriminate subjects for an application based on various signals obtained from physical or behavioral traits, such as fingerprint, face etc. It has several advantages over classical security methods. In biometric system, we don't want to remember large PIN code that may easily forgotten or a key that may lost or stolen [6].

Nowadays fingerprint can be spoofed easily using materials like gelatin, silicon, and wooden glue. Therefore, an effective fingerprint system will have the ability to distinguish a spoof from an authentic finger.

In biometric system liveness detection is used to determine whether the biometric being captured is the actual measurement from an authorized, live person who is present at the time when it is captured. No every system is efficient to prevent all attacks. But these liveness algorithms will reduce the risk of spoofing [3].

Now there are several fingerprint liveness detection algorithms available, and they are mainly classified into two groups: Hardware and software. Hardware consists of a specified device attached to the sensor to detect particular feature of a living traits such as blood pressure, skin distortion, or the odor. Software approach detects fake traits once sample is obtained with a standard sensor [2].
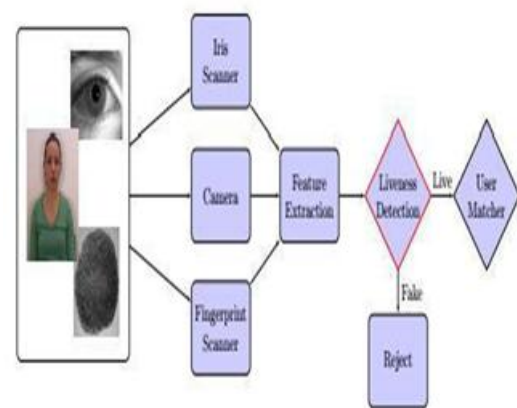
Figure 1: A typical biometric authentication system equipped with a liveness detection module [12].

From the image of fingerprint we will extract the features that we can use to distinguish between real and fake fingers. Some technique uses features such as ridge strength, continuity, and clarity of fingerprint [2]. Result in missing features that degrade the overall performance of the recognition systems [7].

Artificial Neural Networks (ANNs) are computational processing systems inspired from biological nervous systems. ANNs are mainly comprised of a high number of interconnected computational nodes (referred to as neurons), of which work in a distributed fashion to collectively learn from the input in order to optimize its final output. The term convolutional network (CNN) is used to describe an architecture for applying neural networks to two-dimensional arrays (usually images) [9].
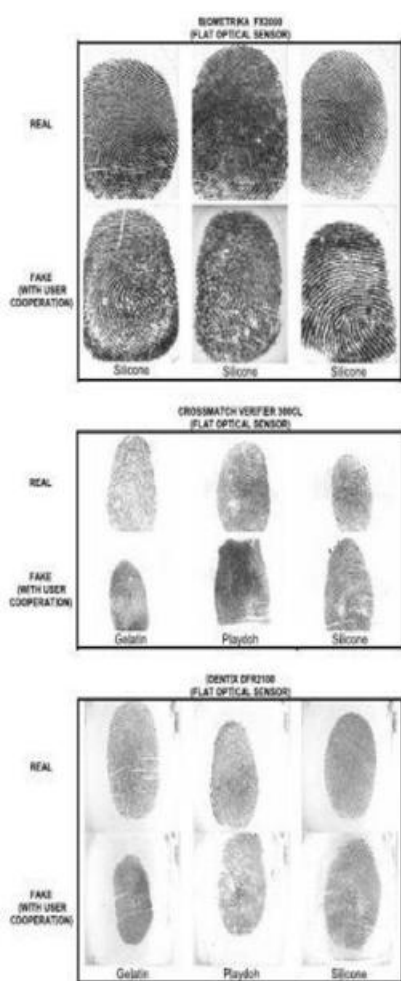
2. Feature Extraction Methods

2.1 Local Binary Patterns (LBP)

LBP operator is an image operator used to transform an image into an array or labels that describes small scale appearance of an image. These labels, commonly known as histograms, are used for further image analysis [4]. LBP was originally proposed for texture description and now

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widely used in many applications such as image/video retrieval, aerial image analysis, and visual inspection. Tolerance against the monotonic illumination changes and computational simplicity are the important properties of LBP features [5][6]. LBP feature selection means how most discriminative LBP features are selected.

LBP are a local texture descriptor and is used in the best current method for fingerprint liveness detection. The original LBP operator assigns a label to every pixel of an image, by considering the 8 neighbors of a 3✗3 – neighborhood and thresholding them with the central pixel value, and thereby outputs a unique 8-bit code representing 256 possible neighborhood combinations. The resulting binary numbers are called LBP or LBP codes [5].Figure 3 shows an example of this operation. Since the comparison is done between the neighborhood and the central pixel value, it is known as illumination invariant descriptor. Neighborhood of different sizes can be used [1][2].


Figure 2: Typical examples of real and fake fingerprint images that can be obtained from the LivDet2009 database used in the experiments [1].

In this survey two feature extraction technique for software – based fingerprint liveness detection: CNN and LBP, and a feature extraction technique for hardware – based fingerprint liveness detection: Fingerprint Pore Characteristics are compared.

LBP is a non-parametric method that efficiently summarizes the local structure of an image [5][6].

Although the performance of fingerprint recognition systems has greatly improved, it is still influenced by many factors. Among these, fingerprint image quality which is a measure of the characteristics of ridge-valley texture, has had the greatest impact on matching performance. Poor quality images mostly
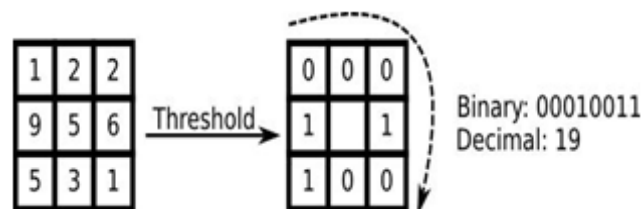
Figure 3: Example showing how the LBP operator works

Another extension to original LBP is called uniform patterns. That can be used to reduce the length of the feature vector and thereby a simple rotation invariant descriptor is implemented. If there are at most two bitwise transitions from 0 to 1 or vice versa in a binary pattern, then they are said to be uniform, only when the bit pattern is considered uniform[1][2][4]. For example, the patterns 00000000 (0 transitions), 00110000 (2 transitions) and 11000111 (2 transitions) are uniform whereas the patterns 11001011 (4 transitions) and 01010100 (6 transitions) are not [4]. In uniform LBP mapping, each uniform pattern will have separate labels and a single label is assigned to all non – uniform patterns. Therefore, there will be P(P-1)+3 different output labels for patterns having P bits. For the neighborhood of 8 sampling points and 16 sampling points, uniform mapping produces 59 and 243 output labels respectively [4].

The normalized histogram of the LBPs forms the feature vector. While computing the histogram we assume that the distribution of pattern matters, but not the spatial location [1][2]. Figure 4 shows an example of how LBP works.

In facial image analysis, the given input image is divided into several small regions, and their LBP histograms are extracted and concatenated to form a spatially enhanced feature vector with O(103) dimensionality. Some recent variations like Extended LBP, VLBP and Gabor Wavelets based LBP, increases the length of feature vector as well. Recently the LBP feature selection has been addressed in many areas. They are broadly classified into two categories: one is to reduce the feature length based on some specific rules while other is to use the feature selection technique to choose the discriminative patterns [6].
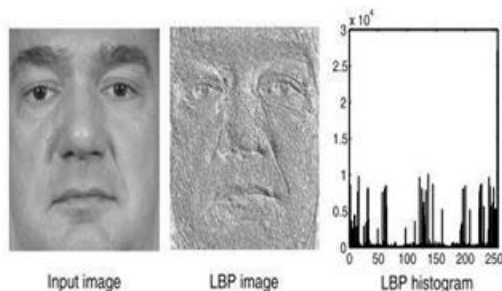
Figure 4: An example of how LBP works [4].

2.2 Fingerprint Pore Characteristics

In Fingerprint Pore Characteristics, characteristics of pores in a fingerprint are used to detect whether it is live or fake, since they are not represented the same in the live or fake fingerprints. First we have to locate the pores, and then the pattern matching is performed on the located pores. The main assumption in this approach is that pores are more likely to appear in live fingerprint than in the fake fingerprint.

Nowadays there are several advanced methods for creating fake fingerprints and thereby qualities of spoofed fingerprints are improved. And also it becomes easier for a skilled imposter to represent pores in a fake finger. So a new alternative is introduced and it analyses the detected pores in terms of their perspiration activity. It is a method to detect active sweat pores using high pass and correlation filtering on images collected using a camera. This approach only uses the supplied gray-scale fingerprint image to classify the sweat pores in a simple and efficient manner. The ability to detect pores is dependent on the resolution of the fingerprint image.

The resolution must be greater than or equal to 1000 dpi so that the pores can be reliably extracted from the fingerprint images [3].

Depending up on whether a pore segregates sweat or not, It can be classified as either open or closed (shown in Figure 5). An open pore is one that segregates and opens into the valley on one side while a closed pore is one that appears as a closed circle in the center of the ridges [3]. We can also define open and closed pore based on the position on ridges. A closed pore is completely enclosed by a ridge, while an open pore is opens into the valley lying between two ridges.

Figure 5: Shows open and closed pores [8].

A number of features can be used to characterize sweat pores in a fingerprint image. One type of feature group is representative of the number of pores detected and the pore-to-pore spacing. Perspiration phenomenon is the key attribute that distinguishes live and fake finger. By analyzing the gray level distribution around the pores we

can find out the perspiration activities of each pore. We already know that a fake finger doesn't emit perspiration, so identifying an open pore indicate that the finger is alive. And also by analyzing the gray level distribution around the pores the diffusion of perspiration coming out of a pore into the surrounding region can be measured. This is done by following a circular path at some radius around the pore center, and pixels in this path are analyzed by calculating their gray level variance and maximum gray level difference. This feature provides robustness when more realistic fake fingers are presented, such as those obtained using the cooperative method [3].

For 2000dpi fingerprint images a pore extraction method using skeletonized image was proposed. A pore is determined as an open (or closed) if that point has 1(or 3) neighbors in the skeletonized image. Because of low resolution (1000dpi) or poor quality of images, this method is highly sensitive to noise and sometimes fails to work. Sudden changes in the intensity values of pore positions from white to black gives high negative frequency response. This sudden changes are captured by applying the Mexican hat wavelet transform to the original image $f(x, y) \in R^2$ to obtain the frequency response w :

$$w(s, a, b) = \frac{1}{\sqrt{s}} \int \int_{R^2} f(x, y) \, \phi\left(\frac{x-a}{s}, \frac{y-b}{s}\right) dx \, dy,$$

where s is the scale factor (+= 1.32) and (a, b) is the shifting parameter. This wavelet is a band pass filter with scale s. After normalizing the filter using min-max rule, pore regions that typically have high negative frequency response are represented by small blobs with low intensities Figure 6(b)).

In order to avoid the misclassification of points in the valleys as pores, it is important to identify ridges from valleys. For that we will apply a Gabor filter enhancement that separates ridges from valleys (Figure 6(c). By simply adding the wavelet response to the Gabor enhanced image, we obtain "optimal" enhancement of pores on the ridges (Figure 6(d)) [8].

The differences between open and closed pores are removed by this procedure and, therefore, the pore extraction process is simplified. Finally, pores with blob size less than 40 pixels are extracted by applying a pre-determined threshold (=58) (Figure 6(e)) [8].

$$D_g(x, y) = max_\theta \left(I\left(x + dcos(\theta), dsin(\theta)\right)\right)$$
$$- \qquad min_\theta \left(I\left(x + dcos(\theta), y + dsin(\theta)\right)\right)$$

After these three characteristics are extracted from fingerprint, we use histograms to represent the distributions. 10 bin histogram is used to represent pore spacing, pore region gray level variance, and pore region maximum gray level difference [3].

Now the Support Vector Machine (SVM) classifier with a radial basis function (RBF) kernel is used to classify whether the extracted feature is live or fake [3][8].
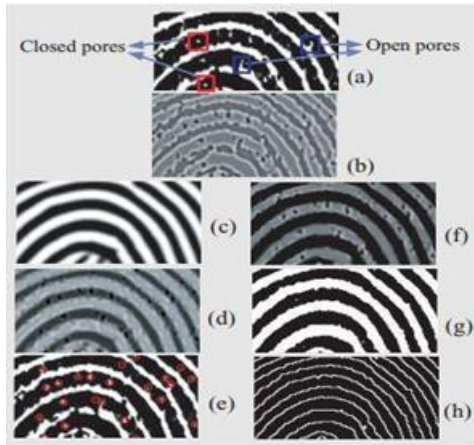
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Figure 6: Level 3 feature extraction [8].

The feature extraction process is summarized as follows: First the inputted fingerprint image is converted into binary image in order to distinguish between ridges from valleys. Then the binary ridge segments are thinned to a single pixel wide skeleton that identifies a centerline for each ridge segment. This skeleton is then followed and the pore searching algorithm is implemented. The threshold can be a constant value for all images or may be pre-computed for each image based on the statistics of the gray level distribution of the image. Once a pore is identified, the statistics of the gray level values in a circular path of radius d around the pore, such as gray level meanm_g, varianceσ_g^2, and maximum gray level difference D_g are analyzed. The distance from the previous pore center to the current one is then measured, giving the pore-to-pore spacing along ridge segments [3].

$$m_g(x,y) = \frac{1}{2\pi} \sum_{\theta=0}^{2\pi} I(x + d\cos(\theta), y + d\sin(\theta))$$

$$\sigma_g^2(x,y) = \frac{1}{2\pi} \sum_{\theta=0}^{2\pi} (I(x + d\cos(\theta), y + d\sin(\theta)) - m_g(x,y))^2$$

2.3 Convolutional Neural Network

Convolutional Networks are the state-of the-art technique in a variety of image recognition benchmarks. A classical Three different types of pooling/sub-sampling are commonly used: average, max and stochastic pooling. Average Pooling outputs the average of the activations units in each patch (shown in Figure 8). Max Pooling outputs the maximum value of each patch (shown in Figure 8). Stochastic Pooling randomly draws a value from each patch based on a distribution where higher pixel values have higher probabilities of being chosen. The patches obtained from the previous convolutional layer are used for pooling process [1].

convolutional network is composed of alternating layers of convolution and local pooling. Common patterns within the local regions of the inputted images throughout the dataset are extracted by the first convolutional layer. For this, a template or a filter is convolved over the pixels of the input image, then for every position in the template inner products at computed and output it as feature map c, for each and every filter in the layer. This output indicates how well the template and each portion of the image match. A non-linear function $f(c)$ is then applied element-wise to each feature map c. The popular choices for $f(c)$ are $\tanh()$ and logistic functions, Here we consider linear rectification as the non-linearity function [1].

Now the resulting activations $f(c)$ are passed to the next layer, ie., the pooling layer. Information within a set of local regions, R, is aggregated and outputs the pooled feature map s. pool () is used to denote this aggregated function. For each feature map:

$$S_j = pool\big(f(c_i)\big) \forall i \in R_j \quad [1]$$

Where R_i is the pooling region j in c and i is the index of each element within it [1].

In a multi-layer model pooled maps are inputted to the convolutional layer and features invariant to local transformations of the input image are extracted [1].

The architecture of the CNN with two layers of convolution weights and one output processing layer is given in Figure 7.
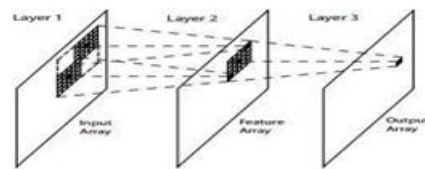

Figure 7: Architecture of a CNN with a single convolutional neuron in two layers [9].
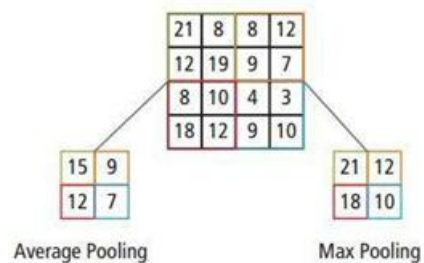

Figure 8: Pictorial representation of max pooling and average pooling [11].

3. Discussion

In order to compare these three techniques five parameters are used. They are

- Training time

- Classification time
- Classification Error(CE)

$$CE = (SFPR + SFNR)/2 \qquad [1]$$

where SFPR (Spoof False Positive Rate) is the percentage of misclassified live fingerprints and SFNR (Spoof False Negative Rate) is the percentage of misclassified fake fingerprints [1].

- SNR
- Accuracy

Table 1: Performance Comparison Table

METHOD	TRAINING TIME	CLASSI-FICA-TION TIME	CLASSI-FICATI-ON ERROR	SNR	ACCU-RACY
LBP	20 mints	<300 ms	9.67 %	Medium	92 %
FINGER-PRINT PORE CHARA-CTERISTICS	Requireno training	>600 ms	12.9 %	Low	Accurate only when used with other techniques
CNN	1.5 hours	<600 ms	4.75 %	High	95.5 %

Table 2: Advantages and Disadvantages

METHODS	ADVANTAGES	DISADVANTAGES
LBP	* Based on acquired sample * Reduce the use of memory space * Cheap * Convenient to embed in hardware * Error rate close to zero at validation time	* Error rate around 50 % at test time * Highly prone to overfitting *Dataset augmentation needed for better result
FINGERPRINT PORE CHARACTERI-STICS	* Based on physiological measures * Use two filters	*Require interventions at the device level * Expensive * Time consuming
CNN	* Simple to implement * Does not require architecture selection * Enhance security system * Overfitting seems not be a problem * 55 % reduction in test error rate * Good material robustness	* NIL

4. Conclusion

Fingerprint Pore Characteristics shows better performance only when used with other fingerprint liveness detection methods. It also provides better performance when used as a stand-alone in cases where an imposter is impossible to retain pores during the fake finger creation.

Convolutional neural networks were used to distinguish between live and fake fingers. Pre-trained CNNs shows state-of-the-art results in various benchmarks. CNN provide best performance than LBP but they are slower to train and are complex to design than others.

But our major concern is about accuracy, so we can conclude that CNN provide better performance than others.

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