SVM Classifier Technique for Fingerprint Based Gender Identification

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Abstract: Skin on human fingertips contains ridges and valleys which together forms distinctive patterns. These patterns are fully developed under pregnancy and are permanent throughout whole lifetime. Prints of those patterns are called fingerprints. Through various studies it has been observed that not two persons have the same fingerprints, hence they are unique for every individual. Fingerprints have remarkable permanency and individuality over the time. Above mentioned properties that human fingerprints have, made them very popular as biometrics measurements. Gender classification from fingerprints is an important step in forensic anthropology in order to identify the gender of a criminal and minimize the list of suspects search. The project deals with the problem of gender classification using fingerprint images. The project proposes a method for identifying the gender using fingerprint based on different features extracted. The relevant features to be extracted that distinguish the gender are ridge thickness to valley thickness ratio (RTVTR), and the ridge density. The extracted features are then used to train support vector machine classifier which can later predict the gender based on the extracted data.

Keywords: SVM, RTVTR, Ridge Density, Biometrics, Radial basis function.

1. Introduction

A successful gender classification approach can boost the performance of many other applications including face recognition and smart human-computer interfaces. Since the credentials can be lost, stolen or duplicated, token-based or knowledge-based approaches for personal identification were not secure [1]. On the other hand, biometrics is a science of verifying and establishing the identity of an individual through physiological features or behavioral characteristics that are unique to the individual and hence cannot be stolen, lost or misused. For successful human identification features used for biometric technique should satisfy certain properties such as they should be available to or within every individual, it should remain unchanged and available all the times and they should be extracted efficiently and accurately and measured quantitatively [2].

Among all the biometrics, fingerprint which is the reproduction of a fingertip epidermis, produced when a finger is pressed against a smooth surface, is the most established and well studied thing. Different studies prove that gender identification from fingerprint images is possible using the three relevant features, i.e. Ridge thickness to Valley thickness ratio (RTVTR), Ridge density and the White lines count. Studies showed that the males have higher ridge count than the females [3]. It was shown that both males and females have higher rightward directional asymmetry in the ridge count with the asymmetry being higher in males than females and higher incidence of leftward asymmetry in females. The above mentioned features are then passed to SVM classifier.

SVM is a learning machine used as a tool for data classification, function approximation, etc, due to its generalization ability and has found success in many applications [4, 5]. Feature of SVM is that it minimizes the upper bound of generalization error through maximizing the margin between separating hyper plane and dataset. SVM has an extra advantage of automatic model selection in the sense that both the optimal number and locations of the basis functions are automatically obtained during training. The performance of SVM largely depends on the kernel [6].

The rest of this paper is organized as follows. Section 2, gives system overview. Section 3, gives a brief description about feature extraction algorithms. The details of SVM classifier used was described in section 4.The experimental results were shown in section 5. Conclusion and future enhancements were given in section 6.

2. System Overview

Figure.1 shows the methodology for gender identification using fingerprint images. Each of the 15 fingerprints of a subject is collected. Pre-processing techniques like binarization and enhancement are performed on the fingerprints in the next stage. The relevant features that can distinguish gender from fingerprints are extracted by applying different image processing techniques . The final step is to train the SVM classifier with the extracted known data values which later classify the unknown fingerprints as a male or female fingerprint.

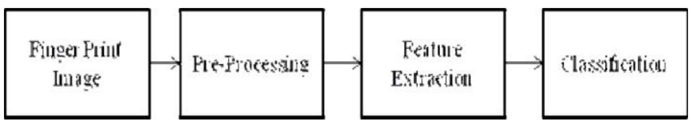

Figure 1. Block Diagram of the overall System

3. Feature Extraction

In pattern recognition and in image processing, Feature extraction is a special form of dimensionality reduction. Transforming the input data into the set of features is called features extraction. If the features extracted are carefully chosen it is expected that the feature set will contain relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

The two major features that are significant for gender classification using fingerprint images are:

- Ridge Thickness to Valley Thickness Ratio (RTVTR).
- Ridge Density.

3.1 Calculation of RTVTR

The RTVTR is the average ratio between the ridge thickness and valley thickness of a fingerprint. RTVTR is an important measure that can be used to classify the gender using fingerprint images. Female subjects are said to have higher RTVTR value compared to male subjects. The fingerprint image is divided into 32x32 non overlapping blocks. The local ridge orientation within each block is calculated. The projection profile of the valleys and ridges along a line perpendicular to the local ridge orientation in each block is calculated, and the projection profile was binarized using 1D optimal thresholding. The resultant binary profile represents the ridges and valleys in this block [7]. The average RTVTR is calculated for each block For each block, a quality index was calculated as the average difference between the values of successive singular points (Minimas and Maximas) of the projection profile, blocks of good quality have higher quality index than those of bad quality.

3.1.1 Finding Local Ridge Orientation

The orientation image represents an intrinsic property of the fingerprint images and defines invariant coordinates for ridges and valleys in a local neighborhood. The quality of the ridge structures in a fingerprint image is an important characteristic, as the ridges carry the information of characteristic features required for minutiae extraction. Ideally, in a well-defined fingerprint image, the ridges and valleys should alternate and flow in locally constant direction. Thus, image enhancement techniques are often employed to reduce the noise and enhance the definition of ridges against valleys.

Normalization is used to standardize the intensity values in an image by adjusting the range of grey-level values so that it lies within a desired range of values [8]. Let N (i, j) represent the normalized grey-level value at pixel (i, j). The normalized image is defined as:

$$N(i,j) = M_0 + \frac{VAR_0\,(I(i,j)-M)^2}{VAR}, \quad if\ I(i,j) > M \tag{1}$$

where M_0 and VAR are desired mean and variance respectively. M and VAR are mean and variance of the image respectively. The mean and variance of a gray-level fingerprint image I of size NxN are,

$$M(I) = \frac{1}{N^2}\sum_{i=1}^{N-1}\sum_{j=1}^{N-1} I(i,j) \tag{2}$$

$$VAR(I) = \frac{1}{N^2}\sum_{i=1}^{N-1}\sum_{j=1}^{N-1} (I(i,j) - M(I))^2 \tag{3}$$

Normalization is pixel-wise operation. It does not change the clarity of the ridge and furrow structures. The main purpose of normalization is to reduce the variation in gray level values along ridges and furrows, which facilitates the subsequent processing steps. Given a fingerprint image G , the main steps of the algorithm to find the local ridge orientation were as follows:

- Divide G into blocks of size w x w (32x32). Let the umber of blocks be N.
- Compute the gradients $\delta_x(i,j)$ and $\delta_y(i,j)$ at each pixel (i,j). The operator used is Sobel operator.
- Estimate the local orientation of each block centered at pixel (i, j) using:

$$\Delta_x(i,j) = \sum_{u=1}^{w}\sum_{v=1}^{w} 2\delta_x(u,v)\delta_y(u,v) \tag{4}$$

$$\Delta_y(i,j) = \sum_{u=1}^{w}\sum_{v=1}^{w} \delta_x(u,v)^2 - \delta_y(u,v)^2 \tag{5}$$

$$\Theta(i,j) = \tan^{-1}\frac{\Delta_y}{\Delta_x} \tag{6}$$

Where $\Theta(i, j)$ is the least square estimate of the local ridge orientation at the block centered at pixel (i, j). Mathematically, it represents the direction that is orthogonal to the dominant direction of the fourier spectrum of the w x w window.

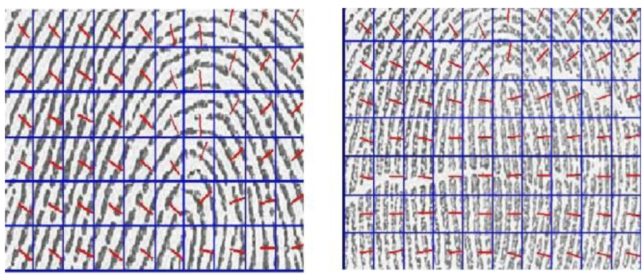

Figure 1. Ridge Orientation for male and female fingerprints

$$\sqrt{\qquad}\;, \; Otherwise$$

VAR

3.1.2 Binarizing the Fingerprint Image

Binarization is process where a grayscale image is decimated or categorized into only two levels, black and white (0 and 1). Since quality of fingerprints is varying, the grayscale image of the fingerprint will be more or less disturbed and noisy. Therefore binarization is performed in a way that it has nhancing effects on the fingerprint image.

Binarization of the fingerprint image is done as a preprocessing step before finding the projection profile. Thresholding is used for binarizing the image. Thresholding is the process of segmenting the image by scanning it pixel by pixel and labeling each pixel as object or background, depending on whether the gray level of that pixel is greater or less than the value of threshold T [9]. The following algorithm is used to obtain T automatically.

1. Select an initial estimate for T.
2. Segment the image using T. This will produce two groups of pixels: G1 consisting of all pixels with gray level values greater than T and G2 consisting of pixels with values ≤ T.
3. Compute the average gray level values **μ**1 and **μ**2 for the pixels in regions G1 and G2.
4. Compute a new threshold value:

$$T = \frac{1}{2}(\mu_1 + \mu_2) \tag{7}$$

5. Repeat steps 2 through 4 until the difference in T in successive iterations is smaller than a predefined parameter T_0.

The binarized fingerprint image is divided into non overlapping blocks of size 32 X 32. The projection profile for each of the block is obtained to find the RTVTR for the block.

3.1.3 Finding the Projection Profile

The horizontal projection profile is the histogram of the number of black pixels along every row of the image. The projection profile will have valleys of zero height between the ridges. The projection profile for all the blocks of the fingerprint is obtained as follows.

Each block is rotated by its local orientation angle. The projection profile of a block is calculated by counting the run of black pixels along the horizontal scan lines for the entire block. The projection profile is further binarized using 1D optimal thresholding to obtain the binary profile [10]. The zero height in the binary profile represent the valleys and the maximum height i.e. the peaks of the histogram represent the ridges. Figure 3 shows a fingerprint block and its projection profile.

The ridge and valley thickness is calculated by counting the consecutive zero values and maximum values respectively. The RTVTR for each block is given by:

$$RTVTR = \frac{ridgethickness}{valleythickness} \tag{8}$$

The obtained values for each block is averaged which gives the RTVTR value for the block. The RTVTR value for N blocks is averaged and this gives the RTVTR value for the fingerprint.

3.1.4 Finding the Projection Profile

The Optimal Thresholding [9] technique in one dimension is used for binarizing the projection profile. Figure. 4 shows a projection profile and its binary profile.

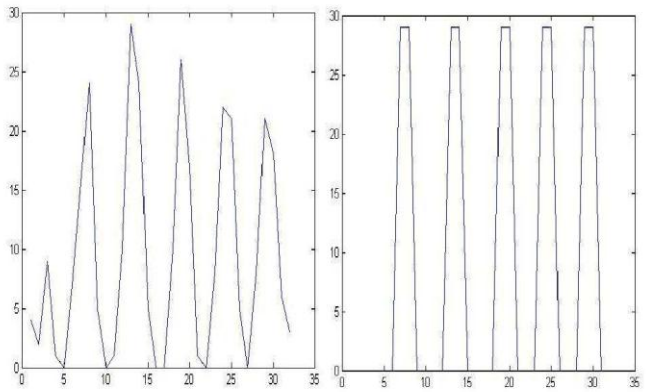

Figure 3. Projection profile and binary profile

The main steps in optimal thresholding technique for images is as follows [9]:

Algorithm

1. Consider as a first approximation that the four corners of the image contain background pixels only and the remainder contains object pixels.
2. At step t, compute $\boldsymbol{\mu}_B^t$ and $\boldsymbol{\mu}_O^t$ the mean background and object gray level, respectively, where segmentation into background and objects at step t is defined by the threshold value T^t determined in the previous step.

$$\mu_B^t = \frac{\sum_{(i,j)\in background} f(i,j)}{\# background\_pixels} \tag{9}$$

$$t = \sum_{(i,j)\in Objects} f(i,\ j) \tag{10}$$

$$\# object\_pixels$$

3. Set

$$T^{t+1} = \frac{\mu_B^t + \mu_O^t}{2} \tag{11}$$

T^{t+1} provides an updated background object distinction.

4. If $T^{t+1}=T^t$ halt else return to step 2.

3.1.5 Finding the Quality Index for the Fingerprint Image Block

The uniformity of ridges and valleys within the blocks varies, for blocks having non uniform ridges and valleys due to the low quality of the fingerprint image in this region, the ridge orientation estimation is usually incorrectly estimated, and thus the RTVTR calculated for this block is incorrect, so only the blocks having the best quality should contribute to the average RTVTR calculated for this fingerprint [8]. For each block, a quality index was calculated as the average difference between the values of successive singular points (Minimas and Maximas) of the projection profile, blocks of good quality have higher quality index than those of bad quality. The blocks were arranged in a descending order based on their quality index, and the RTVTR of the best 20 were averaged and taken as the average RTVTR for the fingerprint. Figures 4 shows the projection profile of a good and bad block respectively.

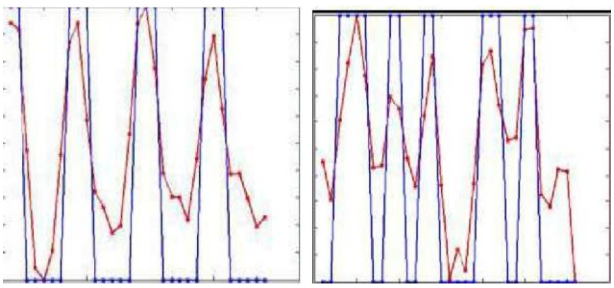

Figure 4. Profile of good and bad fingerprint blocks

3.2 Calculation of Ridge Density

The ridge density is calculated from the projection profile of the blocks that covers the upper portion of the fingerprint. The upper portion of each print was chosen as an area for the data collection because all fingerprint pattern types showed a similar ridge flow in this region [2]. The fingerprint image is enhanced. The enhancement is done in order to clearly define the ridges and valleys so that it will result in flawless counting of the ridges in the region of interest. The number of peaks in the projection profile of the top 128 x 128 block of a fingerprint image is counted, that gives the ridge density for the fingerprint. Fingerprint Enhancement The main purpose of image enhancement is to improve low quality images so that it can avoid the users to re provide their fingerprint just because it is not clearly impressed. A fingerprint image enhancement algorithm receives an input fingerprint image, applies a set of intermediate steps on the input image, and finally outputs the enhanced image. The algorithm for fingerprint image enhancement is given below [7,8].

- Normalization: An input fingerprint image is normalized so that it has a pre specified mean and variance.
- Local orientation estimation: The orientation ima ge is estimated from the normalized input fingerprint image.
- Local frequency estimation: The frequency image is computed from the normalized input fingerprint image and the estimated orientation image.
- Region mask estimation: The region mask is obtained by classifying each block in the normalized input fingerprint image into a recoverable or a unrecoverable block.
- Filtering: A bank of Gabor filters which is tuned to local ridge orientation and ridge frequency is applied to the ridge-and-valley pixels in the normalized input fingerprint image to obtain an enhanced fingerprint image.

4. SVM Classifier

Consider the pattern classifier, which uses a hyper plane to separate two classes of patterns based on given examples {x (i), y (i)} .Where (i) is a vector in the input space $I=R^k$ and y (i) denotes the class index taking value 1 or 0.A support vector machine is a machine learning method that classifies binary classes by finding and using a class boundary the hyper plane maximizing the margin in the given training data. The training data samples along the hyper planes near the class boundary are called support vectors, and the margin is the distance between the support vectors and the class boundary hyper planes. The SVM are based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between assets of objects having different class memberships. SVM is a useful technique for data classification. A classification task usually involves with training and testing data which consists of some data instances [4,5]. Each instance in the training set contains one target value (class labels) and several attributes (features).

Given a training set of instance label pairs (x_i, y_i), i=1… l where x_i €R^{un} and y€$(1,-1)^1$, the SVM require the solution of the following optimization problem:

$$\min_{w,b,\varepsilon} \frac{1}{2} w^T w + c \sum_{i=1}^{l} \varepsilon_i \tag{12}$$

subject to

$$y_i (w^T \phi(x_i) + b) > 1 - \varepsilon_i , \tag{13}$$

$$\varepsilon_i > 0 \tag{14}$$

where C is the capacity constant, w is the vector of coefficients, b a constant. Here training vectors x_i are mapped into a higher dimensional space by the function Ø c alled the kernal. Then SVM finds a linear separating hyper plane with the maximal margin in this higher dimensional space. Thus support vector machines are an innovative approach to constructing learning machines that minimize the generalization error. They are constructed by locating a set of planes that separate two or more classes of data. By construction of these planes, the SVM discovers the boundaries between the input classes; the elements of the input data that define these boundaries are called support vectors.

5. Experimental Results

The two main features were extracted from a dataset of 30 fingerprints containing 15 male subjects and 15 female subjects. Tables 1 brief the results. The results were shown graphically in figures 5.

S*l*. No	RTVTR	Ridge Density	S*l*.No	RTVTR	Ridge Density
1	1.2764	9	1	1.3006	11
2	1.0532	8	2	1.6425	11
3	1.4347	8	3	1.3952	12
4	1.2231	9	4	1.6164	10
5	0.9176	10	5	1.3998	12
6	1.2364	9	6	1.3990	12
7	1.1956	8	7	1.3983	13
8	1.2145	11	8	1.3846	12
9	1.0953	10	9	1.4523	9
10	1.2287	13	10	1.7834	10
11	1.3245	11	11	1.4849	11
12	1.1183	12	12	1.6689	12
13	0.8808	9	13	1.5934	11
14	1.2743	9	14	1.3207	9
15	1.2419	10	15	1.4264	13

Table 1. Feature Values for 15 male and female subjects

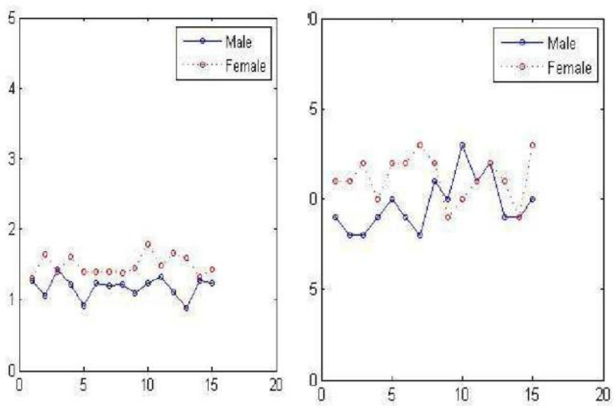

Figure 5. Plot of RTVTR and Ridge Density Values For 15 male and female subjects

From the experimental results it was clear that all the features extracted have higher values in female fingerprints than in male fingerprints. Gender classification results using these dominant features showed that this method could be considered as a prime candidate for use in forensic anthropology in order to minimize the suspects search list and give a likelihood probability value of the gender of a suspect. These extracted features were used to train the SVM classifier with the known result of male or female fingerprints. Further experiments showed that when a new dataset came the SVM classifier can predict the output with an accuracy of 89%.

6. Conclusions and Future Enhancements

This work proposes an SVM based gender classification system using fingerprints. The experimental results indicated that the females fingerprint is characterized by a high RTVTR, while the males fingerprint is characterized by low RTVTR, with the exception of small percentage of males fingerprints having high RTVTR, and females fingerprints having low RTVTR. The study also suggests that females have higher ridge density than males.

The future work is to incorporate additional features such as white line counts in the training as well as classification process and compare the performance of the new system with the existing one.

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