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COMPARISON BETWEEN FEATURE EXTRACTION TECHNIQUES FOR FINGERPRINT BASED GENDER CLASSIFICATION USING KNN CLASSIFIER

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Abstract: Fingerprint based gender classification has gained lot of impetus among the researchers in recent times. It is quite helpful in forensic sciences to narrow down list of suspects. Consequently different researchers have come up with different methods to achieve this. The methods have been based on spatial domain, frequency domain or both. This paper discusses about some of such methods that uses K nearest neighbor classifier for classification and draws comparison between them.

Key Words: gender classification, fingerprint, DWT, SVD, PCA, ridges, KNN;

1. INTRODUCTION

Today's environment demands a reliable personal identification in computerized access control to develop identification and authentication methods for security and organization. This demand has led to the great development in biometric technology. Fingerprint is one of the most established biometric technologies and is considered valid proofs of evidence in courts of law all over the world. Fingerprint carries a lot of information in it that can be exploited in many ways [1]. Fingerprint based gender classification is one of the areas which has attracted lots of researchers in recent times.

Fingerprint is considered highly reliable biometric feature as basic fingerprint patterns do not alter from birth till death unless there is serious injury or there is destruction of dermal papillae. Fingerprint that represents the epidermis of a finger is an arrangement of ridges and valleys which is formed through a combination of genetic and environmental factors. The dermatoglyphic fingerprint patterns are completed by the seventh month of natal development and no further modification can occur. During growth though there is overall increase in palm and hence fingerprint size but no new ridges and ridge breadth are added which is defined as the measurement from the center of one furrow across the ridge to the centre of the next furrow [2].

Fingerprint based gender classification can be useful for anthropologists as they can use the methods for classifying gender from the fingerprints they obtain from excavated articles. It can also

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be helpful for crime investigators in narrowing down the list of suspects [3]. Other than these this classification can also be useful in restricting access to areas permissible to particular gender.

There have been different approaches taken up by different researchers based on spatial and frequency domain analysis. In this paper the comparison between some of such approaches has been taken up. The approaches considered here use K nearest neighbor for classification.

K nearest neighbor (KNN) classifies by finding the Euclidean distance. The testing vector is assigned to the class to which it has minimum distance. K represents the no. of minimum distances to be selected. Generally when there are two groups K (=3 mostly) is taken odd to classify without ties.

2. LITERATURE SURVEY

M.Acree [4] in his work tested if there existed any significant difference in the ridge details of different genders statistically. Females were expected to have finer epidermal ridge detail and males were expected to have coarse ridge detail suggesting higher ridge density in females than in males. Statistical tools like ANNOVA test and turkey test were used to test the hypothesis on 400 samples comprising of 100 samples of African American and 100 samples of Caucasian each for male and female. Results showed that there existed differences in ridge details of male and female fingerprint. The ridge density of males was found to be 11 ridges/25mm^2 or less and females ridge density came out to be 12 ridges/25mm^2.

Ahmed Badawi et.al [5] used features like ridge count, ridge thickness to valley thickness ratio (RTVTR), white lines count, ridge count, ridge count asymmetry and pattern type accordance for the analysis. The classification was done using Fuzzy C-means (FCM), Linear Discriminant Analysis (LDA), and Neural Network (NN) for dominant features. The dataset of 10 fingers for 2200 persons (1100 males and 1100 females) of different age groups was used for analysis which gave 80.39%, 86.5% and 88.5% accuracy for FCM, LDA and NN respectively.

Ritu Kaur et.al [6] worked on gender classification based on frequency domain analysis. FFT, DCT and PSD of the fingerprint image were calculated to obtain the features and depending upon the threshold for each classification was done. The database of 110 males and 110 females from different age groups was used for analysis which gave accuracy of 90% for female and 79.09% for male.

Gnanasivam P and Dr. Muttan S [7] proposed a method using both frequency and spatial domain. The method involved use of discrete wavelet transform (DWT) and singular value decomposition (SVD) for feature extraction and K nearest neighbor (KNN) was used for classification. After being experimented with 1980 male fingerprints and 1590 female fingerprints, the overall classification rate was 88.28%. The success rate for male persons was 91.67% and 84.69% for female persons. Similar approach was taken up by Mangesh K. Shinde et.al [8] and Pallavi Chand et.al [9]. The former experimented with a dataset of 1000 samples and attained overall success rate of 78.46% and 76.84% and 80.46% for female and male respectively. The latter used 100 samples for analysis and claimed to have attained more than 80% success rate. It used more features than the former.

2D Discrete wavelet transform was used in conjugation with principal component analysis and minimum distance method was used for classification. The method was experimented on 200 fingerprints of each male and female and gave success rate of around 70% [10].

Sampta Gupta et.al [3] proposed a method that used discrete wavelet transform for feature extraction and artificial neural network for classification. The method achieved 91.45% classification rate when experimented with database of 550 fingerprints.

Gaussian mixture model was used with discrete wavelet transform and gave 92.67% success rate at 3rd level DWT with 16 Gaussian densities. The methodology was tested on a database of 180 persons comprising of 80 females and 100 males [2].

Suchita Tarare et.al [1] used 6-level Discrete Wavelet Transform for features and KNN classifier for classification. Training was done for 100 fingerprint samples of each male and female and was tested on 30 male and 30 female samples. The success rate obtained was around 70% for female and around 50% for male.

Akhil Anjikar et.al [11] proposed a method that used block-based DCT for feature extraction and K nearest neighbor (KNN) for classification. 512×512 resized fingerprint image was divided into 64 blocks and for each block DCT coefficients were obtained. First coefficient from each block was taken as feature and consequently a feature vector of 64 features was obtained for each fingerprint. The proposed method was tested on 1000 samples of male and female each and the overall success rate for 400 samples for each gender came out to be 55.25%. The success rate for female fingerprints was 65.25% and 45.25% for males

3. GENDER CLASSIFICATION PROCESS

The fingerprint based gender classification process comprises of image acquisition, pre-processing, feature extraction and then classification. Generally a system undergoes training and then the trained database is used for testing and then classification.

Image acquisition process involves acquiring the fingerprint image.

After the image is obtained, it undergoes preprocessing which involves image enhancement, cropping, resizing, noise removal, conversion into binary image etc.

The preprocessed image is then fed to a system for feature extraction. Feature extraction involves spatial and frequency domain methods. Methods based on physical parameters are also considered.

The features are then fed to the classifier for classification.

The feature database is created using this procedure and then using the database as reference fingerprints are classified. Figure1 shows a general gender classification process.

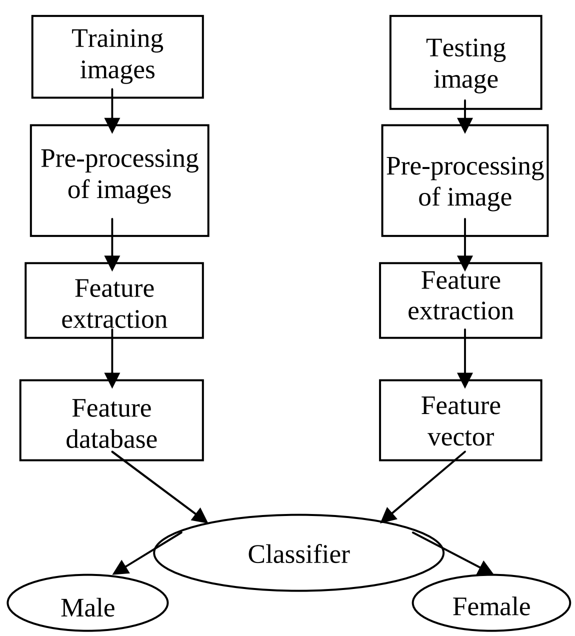

Figure 1. Gender Classification Process

4. METHODS FOR FEATURE EXTRACTION FOR GENDER CLASSIFICATION

This section discusses some of the methods that have been used for feature extraction in gender classification using fingerprint. The approaches discussed here are the ones that used K nearest neighbor (KNN) for classification.

(a) ***Block based DCT:*** Discrete cosine transform (DCT) gives the energy based features of an image. It uses cosine function as its basis and concentrates most of its information in few coefficients. DCT of an image is calculated using the equation (1)

$$F(u,v) = \alpha(u)\alpha(v) \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} \cos\left[\frac{\pi k(2x+1)}{2N}\right] \cos\left[\frac{\pi k(2u+1)}{2M}\right]$$

Where $$\alpha(u)\alpha(v) = \begin{cases} \sqrt{\frac{1}{N}}\ for\ u,v \neq 0 \\ \sqrt{\frac{2}{N}} for\ u,v = 0 \end{cases}$$

Here x and y represents the pixel values of the image of M×N whose DCT is to be calculated.

Block based DCT has been calculated for an image of size 512×512. The image is first divided into blocks of 64×64 and DCT of each block is calculated. The first DCT coefficient from each block is taken to obtain a feature vector of 1×64 size [11].

(b) **DWT based classification:** Discrete wavelet transform is being extensively in image processing for feature extraction, denoising, compression, face recognition etc. Wavelet decomposition decomposes image into four sub-band images namely Low-Low (LL), Low-High (LH), High-Low (HL) and High-High (HH). Most of energy of the image is concentrated in low frequencies and hence the decomposition is generally carried out on LL sub-band for multiple levels. The k-level decomposition gives 3*k+1 sub-bands. The approach discussed here undergoes 6-level decomposition and hence 19 sub-bands are obtained. Energy is calculated for each sub-band using the equation (2) and consequently energy vector of 19 features is obtained [1].

$$E_k = \frac{1}{RC} \sum_{i=1}^{R} \sum_{j=1}^{C} |x_k(i,j)| \tag{2}$$

Here x_k (i,j) represents the pixel value of the k^{th} level sub-band and R,C represents width and height of sub-band respectively.

The preprocessing involves conversion of image acquired into binary and resizing it to 512*512. This image is then fed to extract features and then classification. The approach taken is simple and requires less time. The memory requirements are low too.

(c) ***DWT and SVD based classification:*** The Singular Value Decomposition (SVD) factorizes any rectangular matrix (A) of k×p matrix into product of three matrices (U, S and V).

Where $$A = USV^T \tag{3}$$

$$U = AA^T \tag{4}$$

$$V = A^TA \tag{5}$$

S represents k×p diagonal matrix with r non-zero singular values on the diagonal where r is the rank of A. These diagonal values are the square rooted Eigen values from U or V in descending order. These values form the Eigen vector E which is used as the feature vector.

In [7,8] for the images of size 260×300 pixels the feature vector of SVD is of the size 1×260. The 19 features from 6-level wavelet decomposition of fingerprint image are obtained as in [1]. The combined feature vector is formed by the fusion of 19 DWT features and 260 SVD features. The length of combined feature vector is 1×279.

In [9], the image is of size 512×512 and hence the SVD feature vector is of 1×512 size. The combined feature vector obtained is of length 1×531 (1×19+1×512=1×531).

(d) DWT and PCA based gender classification: Principal component analysis enables to obtain feature vector in spatial domain. It transforms a number of possibly correlated variables into smaller number of uncorrelated variables called principal components. PCA gives data in terms of Eigen vectors computed from the covariance matrix.

512×512 undergoes 6-level wavelet decomposition and 19 features are obtained similar to [1]. Same sized image undergoes PCA to obtain 1×512 sized feature vector. The combined feature vector is of size 1×531(19 +512=531) [10].

5. COMPARISON BETWEEN DIFFERENT METHODS

The approaches discussed in previous section are compared in this section. The comparison is done on the basis of no. of features used which decides the memory requirements of the system, the speed of the system which depends on the type of feature extraction technique used and the accuracy of the system that has been achieved.

(a) ***Memory requirements:*** The memory requirements can be attributed to the length of features used for classification. Lesser the length of the feature vector, lesser the memory requirement, better is the system. The DWT based classification requires minimum features (19). Therefore it has less memory requirements followed by DCT- based classification which requires 64 features. The rest two methods, DWT & SVD based and DWT & PCA based classification have high memory requirements as their feature vector length is around 531. Therefore in terms of memory requirements DWT based classification is the best as it has least length of feature vector.

(b) ***Speed of the system:*** The lesser the time required, higher the speed, better is the system. Generally spatial domain analysis requires more processing time than frequency domain analysis [1]. Thus SVD and PCA based systems have low speed as compared to DWT and DCT based classification. Since SVD and PCA are being used in conjugation with DWT, their speed becomes further less than other discussed methods. Thus it can be concluded that processing time requirement is least for DWT based classification followed by DCT based classification and the rest two, DWT & SVD based classification and DWT & PCA based classification require high processing time.

(c) ***Accuracy:*** The methods discussed here have taken different samples for training and different samples for testing and so it is difficult to comment in terms of accuracy. Only the accuracies of the systems have been enumerated here ignoring the samples used, though increase in sample size may bring variations in the accuracy.

DWT & SVD classification has highest accuracy (88.28%) out of the lot followed by DWT & PCA based classification whose accuracy rate is 70%. The DWT based classification can be considered better then block-based classification because latter used large database still accuracy for the former system which is around 60% is higher than latter whose accuracy is around 55.25%.

Table 1 shows the comparison between the different techniques discussed here on the basis of features, processing time and accuracy.

Table 1
Comparison Between Different Techniques Discussed

Technique used	*No. of features*	*Processing time*	*Accuracy (overall)*
Block based DCT[11]	64	Low	55.25%
DWT [1]	19	Low	around 60%
DWT and SVD [7]	279	High	88.28%
DWT and SVD[9]	531	High	>80%
DWT and PCA[10]	531	High	70%

7. CONCLUSION

This paper discussed about some of the works that used different spatial and frequency domain methods for feature extraction and used K nearest neighbor for classification. Here a comparison was drawn between these techniques on the basis of no. of features, processing time taken and overall accuracy of the system. No. of features were maximum in case of DWT & SVD and DWT & PCA and DWT based classification had 19 features. Processing time was less in case of frequency domain methods which meant DWT and DCT had higher speed than the rest. DWT & SVD managed to attain highest accuracy amongst the rest. Thus the overall performance of DWT based classification and DWT & SVD based classification was good. The former used less number of features and had high speed and latter had high accuracy.

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