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Research Article

An Efficient Fingerprint Based Gender Classification System Using Dominant Un-decimated Wavelet Coefficients

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Abstract: Gender classification is the major and challenging task in the field of forensic anthropology which minimizes the list of suspects search. The existing systems use the availability of bones, teeth and other identifiable body parts having physical features that allow gender and age estimation by conventional methods. The different biometrics traits such as face, gait, iris, speech and fingerprint are used to identify the gender and age. Among the biometrics, fingerprint is most commonly available in any crime scene. In this study, an efficient algorithm to identify the gender of a given fingerprint into male or female is proposed. The two most efficient techniques are utilized to enhance the performance of the gender classification system. As the first step, Un-decimated Wavelet Transform (UWT) is employed to extract the features from the fingerprints by applying ranking. Secondly, Gaussian Mixture Models (GMMs) technique is used as classifier for the process of gender classification. The proposed system is carried out with the database of 180 persons finger prints of all fingers in which 80 are female and 100 are male. The results show the satisfactory classification accuracy of over 90%.

Keywords: Gaussian mixture model, gender classification, stationary wavelet transform, wavelet transform

INTRODUCTION

Over the decades, gender classification is designed based on many human features such as face, teeth, gaits, metatarsals and foot print ratio. But owing their uniqueness and immutability, those features are unsuccessful for gender classification system. Fingerprint images are considered for the proposed approach because each and every person has a unique fingerprint structure and some characteristics like feasibility and reliability. Gender classification system from fingerprint images using features such as ridge count, ridge thickness to valley thickness ratio, white lines count; ridge count asymmetry and pattern type concordance is discussed in Badawi *et al*. (2006). Fuzzy C means, linear discriminant analysis and Artificial Neural Network (ANN) are used for the classification by using the most significant features.

An efficient frequency domain analysis based gender classification using fingerprints is implemented in Kaur and Mazumdar (2012). Fast Fourier Transform (FFT), Discrete Cosine Transforms (DCT) and power spectral density are used in the system. Initially, fingerprint is converted into frequency domain by using the above mentioned techniques and proper threshold value fixed. Depends upon the fixed threshold, the gender classification is performed. An automated gender classification approach by using fingerprints based on Discrete Wavelet Transform (DWT) and Singular Value Decomposition (SVD) is introduced in Gnanasivam and Muttan (2012). The classification is achieved by extracting the energy computed from all the sub-bands of DWT combined with the spatial features of non-zero singular values obtained from the SVD of fingerprint images. K Nearest Neighbor (KNN) is used as a classifier.

A spatial and frequency domain based gender classification by using fingerprint images is illustrated in Gornale *et al*. (2013). It has four major stages, which are image acquisition, pre processing, feature extraction and classification. Before feature extraction, pre-processing steps such as background elimination and cropping process are carried out on acquired images. DWT, DCT, FFT and region properties technique are used to extract salient features such as area, major axis length, minor axis length, eccentricity, orientation, convex area, filled area, Euler number, equivalent diameter, solidity, extent and perimeter. The classification is done by KNN classifier. A novel scheme for gender classification system from fingerprint images is implemented in Purohit *et al*. (2011). AKGEC database along with men and women fingerprint images are used. The mean of all the fingerprints is calculated and the fingerprints are

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normalized with respect to each other. The weight of the each fingerprint is also evaluated and KNN classifier with Euclidean distance measure is used to classify the gender from fingerprints.

An efficient gender classification from fingerprint images is discussed in Wadhwa *et al.* (2013). Scanned fingerprint images are used and the acquired images are converted into gray scale images. Otsu algorithm is applied for binarization. Ridge to valley area and entropy value is calculated from binarized images. The root mean square value is computed from DCT coefficients of fingerprint images. Based on the evaluated parameter, gender classification is performed. An approach for gender classification from fingerprint images based on DWT and ANN technique is introduced in Gupta and Rao (2014). Fingerprint images are acquired from nitgen biometric solution scanner and cropping with background elimination is applied to the acquired fingerprint images. DWT is applied on pre-processed fingerprint images at k-level and the energy feature is extracted from the entire decomposed sub band and stored in database. ANN is used as classifier to classify the gender, whether they are men or women.

A novel gender classification from fingerprint minutiae extraction is discussed in Ponnarasi and Rajaram (2012). Histogram equalization technique is applied to enhance the contrast of images. Pixel-wise wiener filtering is used as a noise elimination technique. Features such as ridge count, Ridge Thickness to Valley Thickness Ratio (RTVTR), fingerprint pattern type, white lines count, pattern type concordance between the corresponding left-right fingerprints and ridge count asymmetry between the left-right corresponding fingerprints are extracted. Support vector machine is used as classifier used to classify the gender from the given fingerprints.

A new technique for gender classification from fingerprint images is presented in Tom *et al.* (2013). DWT and principal component analysis is used for gender classification. In order to obtain the frequency domain features, energy is calculated from decomposed sub bands and spatial features are evaluated by PCA approach. KNN classifier is used for classification. An automated gender classification approach from fingerprint images is introduced in Wang *et al.* (2008). Three fingertip features such as ridge count, ridge density and finger size are considered. The multilayered perceptron classifier is used as a classifier for gender determination.

An automated gender classification scheme from fingerprint images based on DWT and neural network classifier is explained in Bharti and Lamba (2014). DWT is applied to the input training images at 5th level. Energy vector is calculated from the decomposed sub bands and stored in database. Neural network classifier is used to classify the gender of test images comparing with the trained database. A machine learning approach for gender classification is described in Arun and Sarath (2011). RTVTR and the ridge density values are considered as feature vectors. Each image in the fingerprint database is represented by the above mentioned feature vectors and support vector machine is utilized for the classification of gender.

In this study, an efficient gender classification system using UWT and GMM classifier is proposed.

METHODOLOGY

Un-decimated wavelet transform: The un-decimated wavelet transform W using the filter bank (h, g) of a 1-D signal c_0 leads to a set w = $\{\omega_1, \ldots, \omega_J, c_J\}$ where ω_j are the wavelet coefficients at scale are j and c_J are the coefficients at the coarsest resolution. UWT is an inherently redundant approach. The output of each level of UWT contains the same number of samples as the input. The passage from one resolution to the next one is obtained using the "a trous" algorithm (Holschneider *et al*., 1990; Shensa, 1992) (Fig. 1):

$$c_{j+1}[l] = (\bar{h}^{(j)} * c_j)[l] = \sum_k h[k] c_j[l + 2^j k] \quad (1)$$

$$w_{j+1}[l] = (\bar{g}^{(j)} * c_j)[l] = \sum_k g[k] c_j[l + 2^j k] \quad (2)$$

where, $h^{(j)}[l] = h[l]$ if $l/2^j$ is an integer and 0, otherwise. For example:

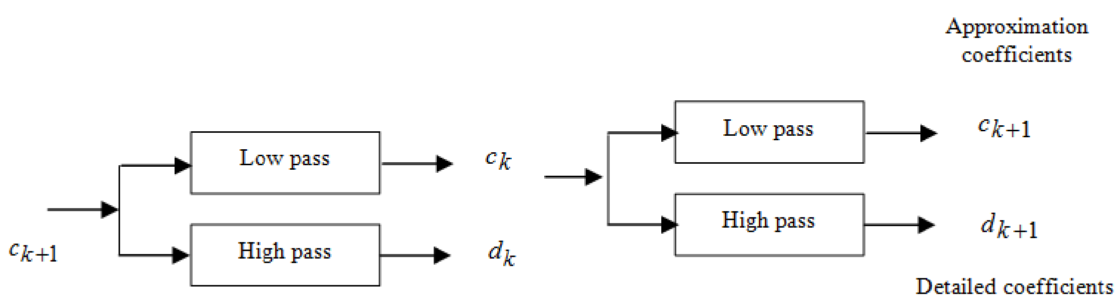

Fig. 1: Filter bank for UWT

$$h^{(1)} = (\dots,\ h[-2], 0, h[-1], 0, h[0], 0, h[1], 0, h[2], \dots) \tag{3}$$

The reconstruction is obtained by:

$$c_j[l] = \frac{1}{2}\left[(\tilde{h}^{(j)} * c_{j+1})[l] + (\tilde{g}^{(j)} * w_{j+1})[l]\right] \tag{4}$$

The filter bank $(h, g, \tilde{h}, \tilde{g})$ needs only to verify the exact reconstruction condition:

$$H(z^{-1})\tilde{H}(z) + G(z^{-1})\tilde{G}(z) = 1 \tag{5}$$

This provides us with a higher degree of freedom when designing the synthesis prototype filter bank. The trous algorithm can be extended to 2-D by:

$$\begin{aligned} c_{j+1}[k,l] &= (\bar{h}^{(j)}\bar{h}^{(j)} * c_j)[k,l] \\ w^1_{j+1}[k,l] &= (\bar{g}^{(j)}\bar{h}^{(j)} * c_j)[k,l] \\ w^2_{j+1}[k,l] &= (\bar{h}^{(j)}\bar{g}^{(j)} * c_j)[k,l] \\ w^3_{j+1}[k,l] &= (\bar{g}^{(j)}\bar{g}^{(j)} * c_j)[k,l] \end{aligned} \tag{6}$$

where, $h_g^* \, c$ is the convolution of c by the separable filter h_g (i.e., convolution first along the columns by h and then convolution along the rows by g). At each scale, three wavelet images w^1, w^2, w^3 are obtained and each has the same size as the original image. The redundancy factor is, therefore 3 (J-1) +1 (Mallat, 1998).

Gaussian mixture models: Gaussian mixture is computed based on the data points in the training dataset belonging to that class. Thus, the likelihood associated with the GMM classifier is:

$$\begin{aligned} l_{GMM}(X|\alpha) &= \log P_{GMM}(X|\alpha) \\ &= \log \sum_{j=1}^{c} \pi \sum_j^{(\alpha)} N(X^b \mu \sum_j^{(\alpha)}, \Sigma_j^{(\alpha)}) \end{aligned} \tag{7}$$

where, C represents the number of components in a Gaussian mixture, N denotes the Gaussian distribution, $\pi_j^{(\alpha)}$ are mixing factors and $\mu_j^{(\alpha)}$ and $\Sigma_j^{(\alpha)}$ represent the mean and covariance of each Gaussian distribution. Note that the subscripted indices mark the Gaussian within the Gaussian mixture of a class, while the superscripted indices indicate the angle class (the corresponding Gaussian mixture).

The fitting of each Gaussian mixture onto the training data points of a given class is accomplished using the Expectation-Maximization (EM) algorithm. This is an iterative general optimization algorithm, whose goal in particular for the GMM is to maximize the likelihood of the training data points with respect to the parameters, consisting of mean and covariance of each component, as well as the mixing coefficients.

An outline of the GMM algorithm is explained below Bishop (2006):

- Initialize the means μ_k, covariance Σ_k and mixing coefficients π_k and evaluate the initial value of the likelihood. The EM algorithm takes many more iteration to reach convergence compared with the K-means algorithm and each cycle requires significantly more computation, we run the K-means algorithm to find a suitable initialization for a Gaussian mixture model that is subsequently adapted using EM.
- **Expectation step:** Evaluate the responsibilities using the current parameter values. The weighting factor for data point x_n is given by the posterior probability (z_{nk}) that component k^{th} was responsible for generating data point x_n:

$$\gamma(z_{nk}) = \frac{\pi_k N(x_n | \mu_{k,\Sigma_k})}{\sum_{j=1}^{k} \pi_j N(x_n | \mu_j, \Sigma_j)} \tag{8}$$

- **Maximization step:** Re-estimate the parameters using the current responsibilities:

$$\mu_k^{new} = \frac{1}{N_k} \sum_{n=1}^{N} \gamma(z_{nk}) x_n \tag{9}$$

$$\mu_k^{new} = \frac{1}{N_k} \sum_{n=1}^{N} \gamma(z_{nk})(x_n - \mu_k^{new})(x_n - \mu_k^{new})^T \tag{10}$$

$$\mu_k^{new} = \frac{N_k}{N} \tag{11}$$

where,

$$N_k = \sum_{n=1}^{N} \gamma(z_{nk})$$

- Evaluate the log likelihood:

$$\ln p(X|\mu, \Sigma, \pi) = \sum_{n=1}^{N} \ln\{\sum_{k=1}^{k} \pi_k N(x_n | \mu_{k,} \Sigma_k)\} \tag{12}$$

- It checks, for the convergence of either the parameters or the log likelihood. If the convergence criterion is not satisfied it returns to the step 2.

This algorithm is applied in the proposed approach to classify the extracted UWT features into male or female.

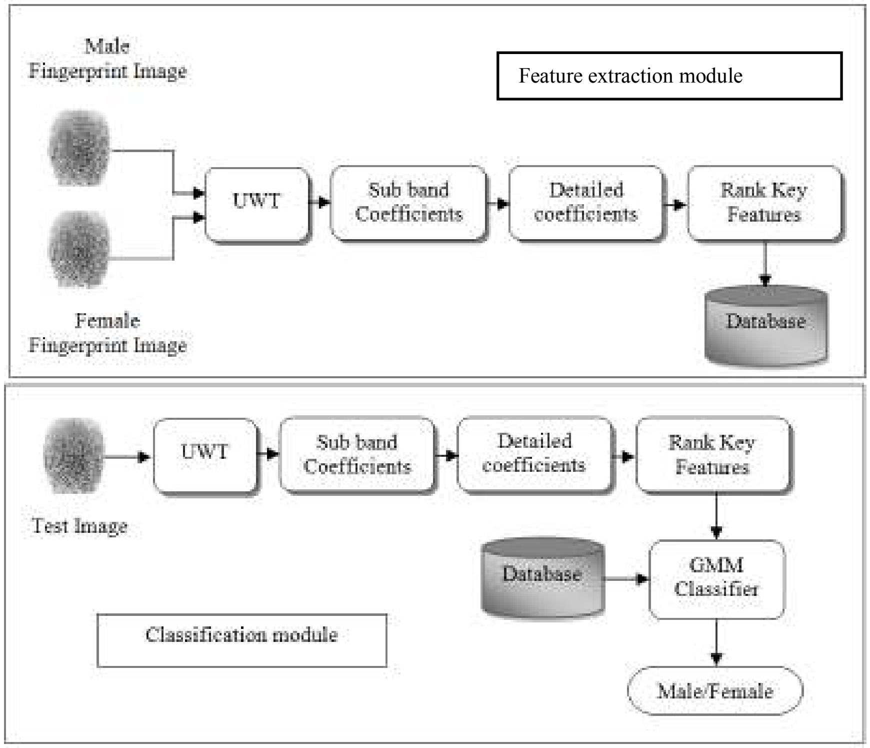

Fig. 2: Automated gender classification system using UWT and GMM

PROPOSED GENDER CLASSIFICATION SYSTEM

The proposed gender classification system using fingerprint images is composed of two major modules named feature extraction and classification. The complete automated system is shown in Fig. 2. In the feature extraction, the UWT coefficients of the fingerprint images are measured as useful features and the supervised learning of GMM is used for classification in the classification module.

In any classification system, feature extraction is an essential pre-processing approach. The first major module of the proposed gender classification system is also a feature extraction module. In this module, the features that best discriminating the gender from the fingerprints using UWT are extracted. At the start, the fingerprint image is represented by the UWT by decomposing it. It provides multi resolution representations of the input fingerprint based on the level of decomposition. This representation contains one approximation sub-band and 3k detailed sub-bands for k level decomposition.

The UWT is an enhancement to DWT in order to mitigate the main disadvantage i.e., lack of translation invariance of DWT. It is achieved by removing the up samplers and down samplers in the DWT. Hence, the output of UWT contains the same number of coefficients as the number of pixels in the input image at each step which require more space for further process and feature extraction might be difficult. To avoid this problem, the high dimensionality UWT coefficients space is reduced by fusion approach and the predefined number dominant features are selected for better classification. The coefficients in the detailed sub-bands are summed together to form a new sub-band. Then, the ranking based coefficients are selected from that sub-band which contains edge information. The t-test class reparability is used to select the dominant UWT coefficients. The obtained top ranked wavelet coefficients are considered as significant features and it stored in database for further classification.

Gender determination is employed in the classification module also named as validation stage. The unknown fingerprint image whose gender has to be classified undergoes the same feature extraction and the selected dominant coefficients are obtained. Then, the obtained dominant features from the test image are compared with feature database by using GMM classifier. In GMM, the probability density functions are modelled as mixtures of 4, 8 and 16 Gaussian densities.

RESULTS AND DISCUSSION

The performance of the proposed gender classification system is carried out on internal database. It includes fingerprints from 100 males and 80 females of different ages. The scanner used to collect the

Table 1: Classification accuracy obtained by the proposed gender classification system using 2nd level UWT decomposition

Size of the input image	Gaussian density	No. of rank features 1	2	3	4	5	6
32×32	4	75.31	77.86	79.15	80.29	81.56	81.22
	8	85.32	86.83	87.78	88.60	89.12	89.41
	16	91.56	92.62	93.01	93.47	93.89	94.16
64×64	4	79.80	82.43	82.02	82.14	82.05	82.66
	8	87.21	89.80	89.81	90.06	90.06	89.43
	16	93.03	93.87	93.88	94.19	93.91	93.89
128×128	4	83.15	82.80	82.88	78.98	75.99	76.51
	8	90.17	90.47	90.20	86.73	83.16	83.23
	16	94.40	94.29	94.63	90.58	86.71	86.72

Table 2: Classification accuracy obtained by the proposed gender classification system using 3rd level UWT decomposition

Size of the input image	Gaussian density	No. of rank features 1	2	3	4	5	6
32×32	4	76.97	79.48	81.48	81.21	82.30	82.71
	8	84.87	88.10	88.76	89.27	90.06	90.86
	16	91.60	93.19	93.84	94.22	94.51	94.60
64×64	4	79.18	80.00	80.22	82.84	80.74	82.29
	8	87.32	88.80	89.12	89.51	90.39	90.06
	16	93.22	93.82	94.07	94.31	94.09	94.53
128×128	4	81.08	80.43	80.70	81.01	81.11	80.41
	8	90.24	89.66	89.56	90.40	89.49	90.23
	16	94.27	94.39	94.58	94.51	94.41	94.50

Fig. 3: All 10 fingerprints of a woman in the database

Fig. 4: All 10 fingerprints of a man in the database

fingerprints from the users is Fingkey Hamster II scanner of resolution 500 dpi. The size of the acquired finger print is 260×300 pixels. As all the fingerprints from each person are collected for the analysis, each and every fingerprint is classified individually. Figure 3 and 4 shows all 10 fingerprints collected from a female and male, respectively.

As the classification system requires training images for female and male category, the whole dataset is divided into two parts by equally splitting it. The splitting is done by random selection. Among the two parts, one part is used for GMM training and another is used for testing. This step is repeated for 10 times and the averaged output is shown in Table 1 and 2 for 2nd and 3rd level of decomposition. To analyze the proposed approach effectively, the size of the fingerprint images are resized to 32×32, 64×64 and 128×128 by bi-cubic interpolation and various density of Gaussian model such as 4, 8 and 16 are used. The performance metric used to analyze the proposed gender classification system is classification accuracy.

From the Table 1 and 2, it is clearly observed that the proposed approach achieves over 90% accuracy while using Gaussian density of 16 irrespective of the level of decomposition used for extracting the features from the UWT decomposed fingerprint images and the number of selected dominant feature is 3. Also, it is noted that the difference between the accuracy obtained by the level of decomposition is accepted. Hence, the proposed approach uses two-level decomposition with Gaussian density of 16 in GMM classifier to classify the gender of the given fingerprint. Figure 5 shows the accuracy of each fingerprint using 128×128 resized fingerprints with 16 Gaussian in GMM. In Fig. 5, F1 indicates the left thumb fingerprint and F5 indicates the left little fingerprint and F6 and F10 indicate the right little and thumb fingerprint.

It is observed from the Fig. 5 that the fingerprints of right ring finger, thumb fingerprint of any hand produces higher accuracy for gender classification than any other fingerprints in the hand. The accuracy obtained while using the fingerprints of little finger is worse than other fingerprints.

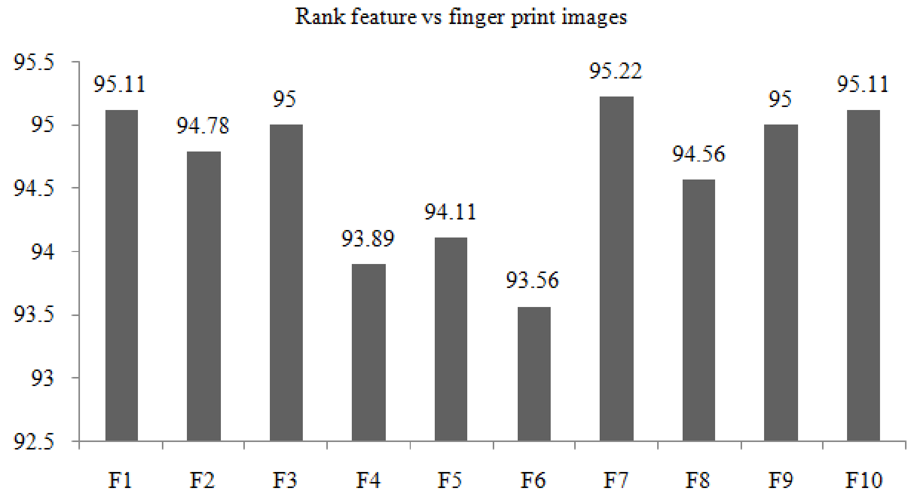

Fig. 5: Accuracy of each fingerprint using 128×128 resized fingerprints with 16 Gaussian in GMM

CONCLUSION

A novel method for automated gender classification using fingerprint images is proposed based on UMT and GMM. The proposed approach is tested by rescaling the input fingerprint images into three different sizes such as 32×32, 64×64 and 128×128 pixels. The fingerprint characteristics are extracted from the UWT decomposed sub bands by fusion and applying t-test class ranking to select the dominant UWT coefficients. The classification performance is measured as the percentage of fingerprints classified into the correct gender class. In order to find the most suitable resolution level at which the feature set may provide best discrimination, different levels of resolution are analyzed. Also, the system is evaluated by various level of Gaussian density. The results show that the maximum classification accuracy is obtained at 3rd level of UWT decomposition of 128×128 resized input image with 16th Gaussian density used by GMM classifier.

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