**GENDER AND AGE AUTHENTICATION AND CLASSIFICATION USING FINGERPRINT**

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***Abstract***

**The forensic investigators always search for fingerprint evidence which is seen as one of the best types of physical evidence linking a suspect to the crime. The image is enhanced using Contourlet Based Transform (CNT).Discrete Wavelet Transform (DWT), the Singular Value Decomposition (SVD) and Principal Component Analysis (PCA) has been used to extract the features and estimate a person’s age using his/her fingerprint. K nearest neighbor (KNN) is used for classification. The evaluation of the system is carried on using real time database of male and female fingerprints. Tested fingerprint is grouped into any one of the following five groups: upto 12, 13-18, 19-24, 25-35 and 36 and above. The sample database is taken with the value of both male and female. The objective of this paper is to identify whether it belong to male or female and determine the corresponding age.**

***Keywords:*** *Gender Classification, Fingerprint, Contourlet Based Transform, Discrete WaveletTransform, Singular Value Decomposition, Principle Component Analysis,k nearest neighbor.*

**1. Introduction**

Digital image processing is the use of digital computers to edit digital images. Digital Image processing has various steps for processing the image and will perform Object Recognition. The act of giving an object a name (such as "vehicle") based on its descriptors is known as recognition. Many human body features have been used to estimate sex/gender. Some of recent examples include footprint ratio, metatarsals, humerus, long bones of the arm, foot shape,  femoral head, foot and shoe dimensions, patella, teeth and radial and ulnar bone lengths. Humans are uniquely identified by means of biometric identification technologies, mostly for identification and verification. Due to their uniqueness and ability to remain constant across an individual's lifetime, fingerprints have been utilized as a biometric for the identification of gender and age [1].

In order to generate investigative leads for locating elusive individuals, gender and age information is crucial. It's crucial to offer information about the gender and age of potential suspects as well as any other relevant details. Existing methods for gender classification have limited use for crime scene investigation. The spatial distortions are well handled by transform domain approaches such as Laplacian Pyramid Transform (LPT), Discrete Wavelet Transform(DWT), Curvelet Transform (CT) and Contourlet Transform (CNT) etc In this study, DWT, SVD, and PCA are used to extract a person's gender and age from their fingerprint. In fingerprint, the primary dermal ridges (ridge counts) are formed during the gestational weeks 12-19 and the resulting fingerprint ridge configuration (fingerprint) is fixed permanently [2-3]. The patterns of ridges on our finger pads are unique: no two individuals, including identical twins have fingerprints that are not same. Also, the variability of epidermal ridge breadth in humans is substantial [4]. Features of dermatoglyphics statistically vary by gender, ethnicity, and age categories [5]. It is proved by various researchers; a fingerprint can be processed for the sex determination [6-11]. Figure 1 illustrates the process of CNT, DWT, SVD and PCA based gender classification using KNN.

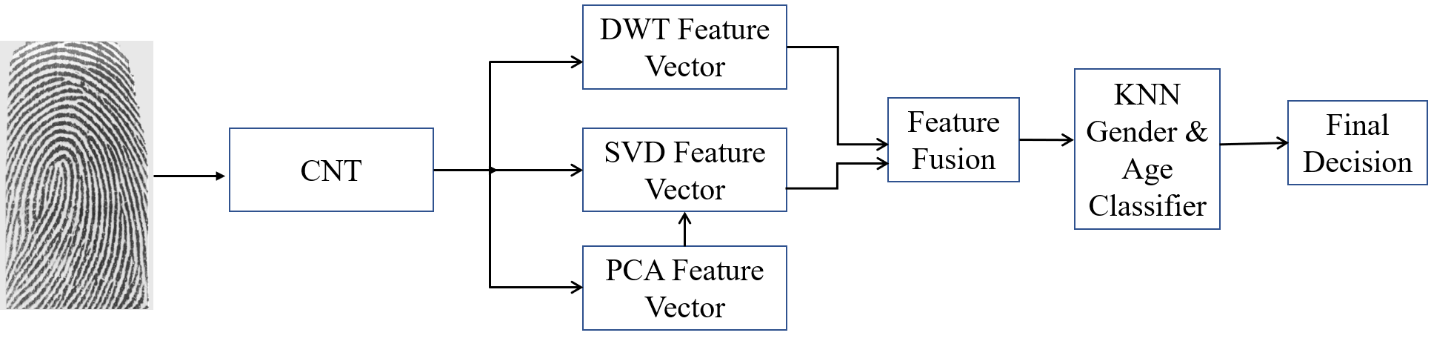


Fig.1 CNT, DWT, SVD and PCA based gender classification system.

Wavelet transform is a transform. Its provides the time frequency representation. In this work Discrete Wavelet transform used for gender classification.

The remainder of this paper flows as follows. The Literature Survey on Gender Classification is reviewed in Section 2. Preprocessing is done in Section 3. Followed by feature extraction in Section 4. Experimental setup and result are discussed in Section 5.

**2. Literature Survey**

The ridge density is greater for females than males, according to earlier research on gender classification based on the ridge density [7,8, 10, 11] and [9], which examined the fingerprints of a tribal population in Andhra Pradesh (India) and made it clear that males had higher mean ridge counts than females. Analyzed is a novel method of identification that makes use of simultaneously captured images of the surface and vein of the finger. In order to combine the matching scores for finger vein and finger texture, this research studies two new score level combination methodologies, namely holistic and nonlinear fusion [12]. Using solely DWT and SVD, a novel approach for gender classification of fingerprint pictures has been developed [13]. A person's identity is verified using their fingerprint biometric. It is suggested to identify domains based on their transform fingerprints. The Fingerprint has been preprocessed to a size that is appropriate for DTCWT. Applying DTCWT at various degrees results in the fingerprint traits.[14].

**3.1 IMAGE ACQUISITION**

Data gathering from multiple imaging modalities is a crucial task for any system area. The first phase in any image processing project is called picture acquisition, and it entails gathering original input image data from the original source (where an image can be found). Image acquisition can be used in a variety of ways.

**3.2 IMAGE PREPROCESSING**

**NOISE REMOVAL**

The goal of preprocessing the datasets is to prepare it in a compatible format for machine literacy and to enhance the quality of the image by removing noises. Noise refers to variation in intensity or brilliance in an image. It might get added during the accession of the images, which is introduced by camera flash, change in illumination, noise background of the image. The purpose of image pre-processing is to remove noise from the image for enhancing the quality of the input image, getting a maximum accurate result, and good effectiveness.

**NORMALIZATION**

The essential preprocessing step of normalisation decreases the colour and intensity variances found in stained images from various laboratories. Research from the last 20 years has shown that stain normalisation greatly improves the accuracy of the unseen dataset by about 8% [16]. The images used in this study were taken from a preexisting dataset of human blood cells that had been processed for laboratory analysis. The smear slides are made in the lab using multiple chemical stains, which causes colour variance because different chemicals are used and different staining techniques are used. The model's ability to learn and deal with more complicated models with a variety of images is hampered, which increases the mistake rate. A solution to standardize this is normalization. By converting the input data to a common space, the Stain Normalisation preprocessing technique aims to reduce colour variability and enhance algorithm generalisation. No matter the scanning technology, stain vendor, or preparation procedures, regions of digital tissue specimens are mapped to equivalent colour characteristics in stain normalised digital pathology samples. Stain Normalisation has shown improvement in computer-assisted diagnostic tools due to the decreased variability in tissue colour features [17, 18, 19]. In their article, Cimopi et al. [15] have shown how methods like histopathology [20] and stain normalization can improve the classification of colorectal tissues in colorectal cancer [10].

**CONTOURLET TRANSFORM**

The wavelet transform excels at identifying discontinuities at object edges but fails to pick up on edge smoothness. Additionally, it can only record a limited amount of directional data. The shortcomings of wavelet can be successfully overcome via contourlet transformation. A discrete image framework with several scales and directions is called a contourlet transform.

In this transform, the multi- scale analysis and the multi-direction analysis are separated in a serial way. The universal contourlet transform uses a double filter bank construction to get the smooth contours of images. In this double filter bank, the point discontinuities are first captured by the Laplacian pyramid (LP), and then they are transformed into linear structures by a directional filter bank (DFB).

In a multidimensional signal processing that can prevent frequency scrambling, the Laplacian pyramid (LP) decomposition only yields one band-pass image. Additionally, because it will leak low frequency signals in its directional sub-bands, directional filter banks (DFB) are only suitable for high frequency applications. Because of this, DFB and LP are combined via multiscale decomposition and low frequency reduction. In order to obtain band-pass signals and send those signals through DFB to capture the directional information of the image, image signals travel through LP sub-bands [21]. When dealing with curves, contourlet transform is more accurate than wavelet transform.

It's a make over that decomposes a given signal into a number of sets, where each set is a time series of portions describing the time elaboration of the signal in the corresponding frequence band. The smooth contours of a picture are obtained via the contourlet transform, which employs a double filter bank construction.

**Steps for Image Enhancement**

Input : Real Time Fingerprint Images

Output : Enhanced preprocessed images

1) Read the images from the Dataset

2) Remove the noise from the images

3) Apply Normalisation

4) Apply CNT

**3.3 FINGER PRINT FEATURE EXTRACTION**

For any pattern recognition, Feature extraction is fundamentally needed. For Feature extraction we have used the techniques of DWT, SVD and PCA. These techniques are discussed below.

**3.1 DWT based Feature Extraction**

A data vector with a length that is an integer power of two can be transformed into a new vector with the same length using the DWT linear operation. It is a tool that divides data into various frequency components and analyses each one with resolution that is appropriate for its scale. Decompose the image using a 2D wavelet transform into 4 subbands. That is High-low, High-High, Low-low, and Low-high. Most of the energy presented in Low frequency. Since Low-Low energy band gives more information it is taken for applying decomposition applied. The energy of each subband is calculated by using the equation (1)

Ek …..(1)

Xk(i,j) 🡪 which is the pixel value of thee kth subband.

R,C 🡪 which is the height and width of the subband.



DWT

Extraction of sub-band energy vector

Fig.2 DWT based Feature Extraction.

**SVD based Feature Extraction**

A general rectangular M by N matrix A has a singular value Decomposition(SVD) into the product of an M by N orthogonal matrix U, an N by N diagonal matrix of singular value S and the transpose of an N by N orthogonal square matrix V,

A= U S Vᶺ T



SVD

Extraction of non-zero Singular values

Fig.3 SVD based Feature Extraction.

Calculate the eigen vector(V) using the equation(2)

[U S Vᶺ]=SVD(X) ----- (2)

**PCA based Feature Extraction**

The features are the principle components are orthogonal to each other and produce orthogonal weights.PCA is great for high dimensional data.

[V E] = eig( cov(X) );

[E order] = sort(diag(E), 'descend');

V = V(:,order);



PCA

Extraction Eigen vector

Fig.4 PCA based Feature Extraction.

The eigenvectors of the covariance matrix V are the principal components and the corresponding eigenvalues E represent the amount of variance explained.

**Fusion**

The features extracted using the PCA is combined with SVD as both the techniques are closely related. Combine the feature vectors, subband energy vector(E), Eigen Vectors to form the feature vector for the training fingerprint. For example if an image size 500\*550, then the subband energy vector size is generated as per the levels choosen and the eigen vector for PCA is 1\*500. Then the resultant feature vector is of size 1\*500+ as per the different levels choosen for performing DWT.

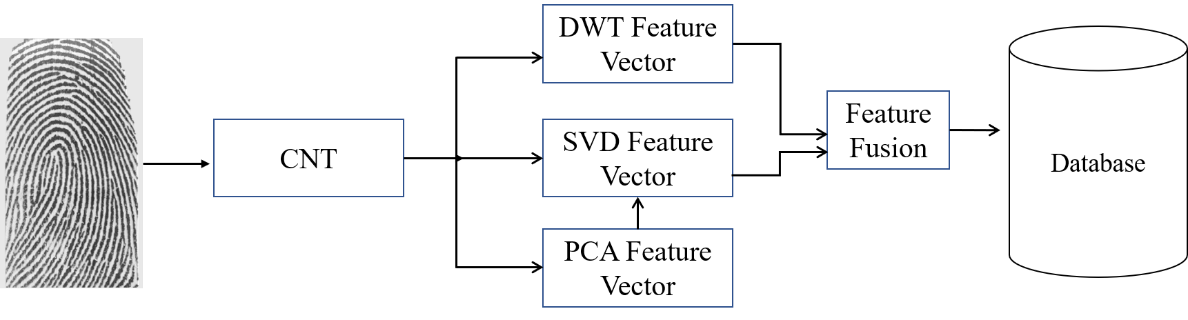


Fig.5 Gender and Age Classification System

The feature vector contains the unique features of the fingerprints to be used for identification. The feature vectors for all the training set images are stored as a reference vector. If training set has ‘n’ number of images then the resultant vector is formed with ‘n’ number of rows with each row representing the feature vector of each training image. The number of columns represents the individual feature of the image vector for reference during the classification. The images are grouped from 1 to 10 as.

Table 1: Sample wise Details for Gender and Age

|  |  |  |
| --- | --- | --- |
| **Gender** | **Age Group** | **Group** |
| F | Upto 12 | 1 |
| F | 13-18 | 2 |
| F | 19-24 | 3 |
| F | 25-35 | 4 |
| F | 36 and above | 5 |
| M | Upto 12 | 6 |
| M | 13-18 | 7 |
| M | 19-24 | 8 |
| M | 25-35 | 9 |
| M | 36 and above | 10 |

**KNN Classifier**

KNN classifies the sample image with reference to the trained vector stored. The images are classified using the trained set along with the grouping made in the previous step.

K nearest neighbor is used for classifying objects based on closet training examples in the feature space. The function used for Knn classification is as follows.

Class=knnclassify(sample,training,Group)

Sample 🡪 Testing image matrix

Training 🡪 Already trained fingerprint images.

Group 🡪 Vector whose distinct values define the grouping of the rows in training.

**Classification Algorithm**

Input : unknown fingerprint and the

feature database

Output : The class of the fingerprint to which this

unknown fingerprint is assigned

1) Decompose the preprocessed fingerprint images with different levels of decomposition using DWT.

2) For each Level calculate the sub-band energy vector (E) using (2).

3) Extract the non zero singular values using SVD.

4)Calculate the Eigen Vector for PCA(V1) using (3)

5) Fuse the Eigen Vector for PCA with the values extracted using SVD.

6) Combine the vectors E,V and V1 to form the feature vector for the given training fingerprint.

6) Apply KNN classifier and find the class of the unknown fingerprint by using the database generated using the previous steps.

**4. Experimental Result**

**Data Set**

The fingerprint images of internal database were collected by using fingerprint machine digital persona 4100. The database includes 200 hand thumb impressions collected from males and females of different ages. The database consists of gray scale fingerprint images. The size of the image is 100 x 110. The number of female fingerprint images is greater than the number of male fingerprint images. For the experiments we considered only thumb finger, middle finger and pointing finger at the finger scanning device could not sense the ring finger and the little finger accurately.

The collected fingerprint images are classified into various groups as specified in Table 1.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Left Hand** | | | **Right Hand** | | |
| **S.No** | **Thumb Finger** | **Pointing Finger** | **Middle Finger** | **Thumb Finger** | **Pointing Finger** | **Middle Finger** | |
| **F UPTO 12** | 60 | 70 | 80 | 70 | 80 | 70 | |
| **F 13- 19** | 80 | 60 | 80 | 60 | 80 | 60 | |
| **F 20 – 25** | 60 | 70 | 70 | 70 | 70 | 70 | |
| **F 26 – 35** | 80 | 60 | 70 | 60 | 70 | 70 | |
| **F 36 & above** | 80 | 80 | 80 | 80 | 80 | 70 | |

Table2. Gender and Age Classification using CNT, DWT, PCA and SVD for male

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Left Hand** | | | **Right Hand** | | |
| **S.No** | **Thumb Finger** | **Pointing Finger** | **Middle Finger** | **Thumb Finger** | **Pointing Finger** | **Middle Finger** | |
| **M UPTO 12** | 70 | 70 | 80 | 70 | 80 | 70 | |
| **M 13- 19** | 80 | 60 | 80 | 60 | 80 | 70 | |
| **M 20 – 25** | 80 | 70 | 70 | 70 | 70 | 60 | |
| **M 26 – 35** | 60 | 60 | 70 | 60 | 70 | 60 | |
| **M 36 & above** | 80 | 80 | 80 | 80 | 80 | 70 | |

Table3. Gender and Age Classification using CNT, DWT, PCA and SVD for Male

The above table 2 and table 3 shows the classification accuracy of female and male for the fingerprint of thumb finger, pointing finger and middle finger for different age group. The result that the right thumb fingerprint shows the better result for female gender identification and left hand middle fingerprint shows the better result for male identification. Regarding the age group classification, the group 5 and 10 shows better accuracy than other age groups.

**Conclusion**

In this work, we have proposed a method to perform fingerprint gender and age classification by comparing the various features extracted from enhanced images using CNT. The features are extracted using SVD, DWT and PCA techniques. Knn classifier is used for gender classification. It shows better result for both adult male and female. It shows better result for the right thumbprint for female and left middle fingerprint for male. This gender classification can be applied for the academic data of the student and the performance can be analyzed. It can also be extended to classify the transgender.

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