Estimation of Age Through Fingerprints Using Wavelet Transform and Singular Value Decomposition

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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. In this paper discrete wavelet transform (DWT) and the singular value decomposition (SVD) has been used to estimate a person's age using his/her fingerprint. The most robust K nearest neighbor (KNN) used as a classifier. The evaluation of the system is carried on using internal database of 3570 fingerprints in which 1980 were male fingerprints and 1590 were female fingerprints. Tested fingerprint is grouped into any one of the following five groups: up to 12, 13-19, 20-25, 26-35 and 36 and above. By the proposed method, fingerprints were classified accurately by 96.67%, 71.75%, 86.26%, 76.39% and 53.14% in five groups respectively for male and by 66.67%, 63.64%, 76.77%, 72.41% and 16.79% for female. Finger-wise and Hand-wise results of age estimation also achieved.

Keywords: Age Estimation, Discrete Wavelet Transform, Singular Value Decomposition, K-Nearest Neighbor.

1. INTRODUCTION

Age information is important to provide investigative leads for finding unknown persons. Existing methods for age estimation have limited use for crime scene investigation because they depend on the availability of teeth, bones, or other identifiable body parts having physical features that allow age estimation by conventional methods. In this paper, age of a person is estimated from the fingerprints using DWT and SVD. The science of fingerprint has been used generally for the identification or verification of person and for official documentation. Fingerprint analysis plays a role in convicting the person responsible for an audacious crime. Fingerprint has been used as a biometric for the gender and age identification because of its unique nature and do not change throughout the life of an individual [1].

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]. Ridges and their patterns exhibit number of properties that reflect the biology of individuals. Fingerprints are static and its size and shape changes may vary with age but basic pattern of the fingerprint remains unchanged. Also, the variability of epidermal ridge breadth in humans is substantial [4]. Dermatoglyphic features statistically differ between the sexes, ethnic groups and age categories [5]. Gender and age determination of unknown can guide investigators to the correct identity among the large number of possible matches.

According to 'Police-reported crime statistics in Canada, 2010 [6], Crimes tend to be disproportionately committed by youth and young adults and the rate of those accused of a *Criminal Code* offence peaked at 18 years of age and generally decreased with increasing age. As per the publication of 'crime in India statistics-2010, published by National Crime

Records Bureau [7], the crime rate is higher for the age range of 18 to 44 and decreases after 44. Thus the age estimated is categorized in to any one of the five groups: up to 12, 13-19, 20-25, 26-35 and 36 and above. The features of the fingerprints grouped are trained and classified using the KNN classifier. Figure 1 illustrates the process of DWT and SVD based age estimation method.

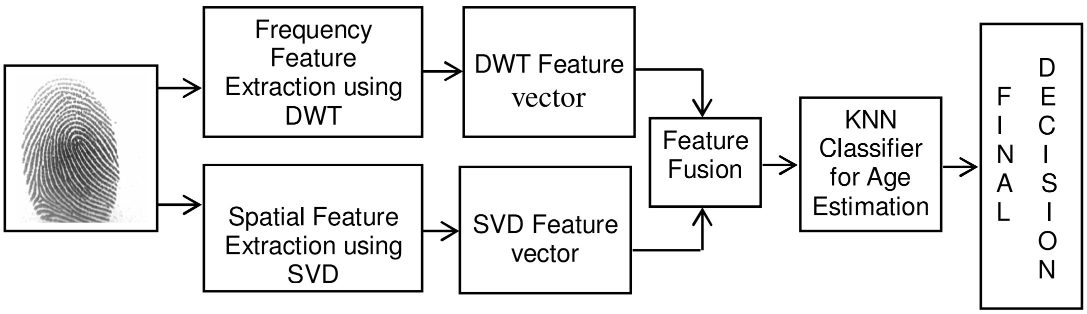


FIGURE 1: DWT and SVD based age estimation method

Only few works were concentrated in the age estimation using the fingerprint. In the view of protecting children from accessing online sites that are harmful to minors, John D Woodward, testified before a hearing of 'commission on online child protection' [8]. According to him, there are no age verification biometrics, no age determination biometrics and no age estimation biometrics. Based on the fingerprint ridge width the age and sex were determined [4]. Many Earlier works were related the fingerprint image quality and the age of a person [9-11]. Other works in the way of age estimation used the speech recognition [12], face [13-15] etc. In this work, authors proposed a method of identifying range of the age using the discrete wavelet transform and the singular value decomposition

Wavelet transform is a popular tool in image processing and computer vision because of its complete theoretical framework, the great flexibility for choosing bases and the low computational complexity [16]. As wavelet features has been popularized by the research community for wide range of applications including fingerprint recognition, face recognition and gender identification using face, authors have confirmed the efficiency of the DWT approach for the gender identification using fingerprint.

The SVD approach is selected for the gender discrimination because of its good information packing characteristics and potential strengths in demonstrating results. The SVD method is considered as an information-oriented technique since it uses principal components analysis procedures (PCA), a form of factor analysis, to concentrate information before examining the primary analytic issues of interest [17]. K-nearest neighbours (KNN), gives very strong consistent results. It uses the database which was generated in the learning stage of the proposed system and it classifies genders of the fingerprints.

The outline of this paper is as follows: the fingerprint feature extraction using DWT and SVD is described in Section 2; we then proposed the age classification using fingerprint features in Section 3; the experimental results are presented in Section 4; Section 5 comes to the conclusion and future work.

2. FINGERPRINT FEATURE EXTRACTION

Feature extraction is a fundamental pre-processing step for pattern recognition and machine learning problems. In the proposed method, the energy of all DWT sub-bands and non-zero singular values obtained from the SVD of fingerprint image are used as features for the estimation of age. In this section, DWT and SVD based fingerprint feature extractions are described.

2.1 DWT Based Fingerprint Feature Extraction

Wavelets have been used frequently in image processing and used for feature extraction, de-noising, compression, face recognition, and image super-resolution. Two dimensional DWT decomposes an image into sub-bands that are localized in frequency and orientation. The decomposition of images into different frequency ranges permits the isolation of the frequency components introduced by "intrinsic deformations" or "extrinsic factors" into certain sub-bands. This process results in isolating small changes in an image mainly in high frequency sub-band images. Hence, discrete wavelet transform (DWT) is a suitable tool to be used for designing a classification system.

The 2-D wavelet decomposition of an image is results in four decomposed sub-band images referred to as low–low (LL), low–high (LH), high–low (HL), and high–high (HH). Each of these sub-bands represents different image properties. Typically, most of the energy in images is in the low frequencies and hence decomposition is generally repeated on the LL sub band only (dyadic decomposition). For k level DWT, there are (3*k) + 1 sub-bands available. The energy of all the sub-band coefficients is used as feature vectors individually which is called as sub-band energy vector (E). The energy of each sub-band is calculated by using the equation (1).

$$E_K = \frac{1}{RC}\sum_{i=1}^{R}\sum_{j=1}^{C}\left|x_k(i,j)\right| \quad (1)$$

Where x_k *(I, j)* is the pixel value of k^{th} sub-band and R, C is width and height of the sub-band respectively.

Figure 2 shows the block diagram of the frequency feature extraction by using DWT. The input fingerprint image is first cropped and then decomposed by using the DWT. For level 1, number of subbands are 4 and 3 subbands are added for each next levels Thus the increase in levels of DWT increases the features.

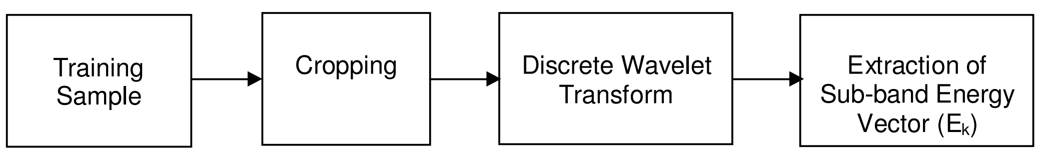


FIGURE 2: DWT based fingerprint feature extraction

2.2 SVD Based Fingerprint Feature Extraction

The Singular Value Decomposition (SVD) is an algebraic technique for factoring any rectangular matrix into the product of three other matrices. Mathematically and historically, it is closely related to Principal Components Analysis (PCA). In addition it provides insight into the geometric interpretation of PCA. As noted previously, the SVD has long been considered fundamental to the understanding of PCA.

The SVD is the factorization of any (k x p) matrix into three matrices, each of which has important properties. That is, any rectangular matrix A of k rows by p columns can be factored into U, S and V by using the equation (2).

$$A = USV^T \quad (2)$$

Where

$$U = AA^T \quad (3)$$

$$V = A^T A \quad (4)$$

And S is a (k x p) diagonal matrix with r non-zero singular values on the diagonal, where r is the rank of A. Each singular value is the square root of one of the Eigen values of both AA^T and A^TA. The singular values are ordered so that the largest singular values are at the top left and the smallest singular values are at the bottom right, i.e., $s_{1,1} \geq s_{2,2} \geq s_{3,3}$ etc. Among the three rectangular matrices, S is a diagonal matrix which contains the square root Eigen values from U or V in descending order. These values are stored in a vector called Eigen vector (V). As the internal database contains images of size 260x300 pixels, the feature vector of SVD is of the size 1x260. The spatial feature extraction by using SVD is shown in Fig 3.

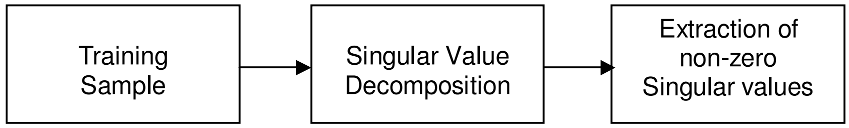


FIGURE 3: SVD based fingerprint feature extraction

3. FINGERPRINT AGE ESTIMATION

The proposed system for age estimation is built based on the concatenation of fingerprint features obtained by using DWT and SVD. This section describes two different stages named as learning stage and classification stage and the KNN classifier used for the age classification.

4.1. Learning Stage

The feature vector V of size 1x260 obtained by SVD and the sub band energy vector E of size 1x19 obtained by DWT are fused to form the feature vector and used in the learning stage. The fusion of feature vector V and E is done by concatenation of features that are widely used for feature level fusion. The resulting feature vector is of the size 1x279 (1x260 +1x19).The learning stage is shown in Fig 4.

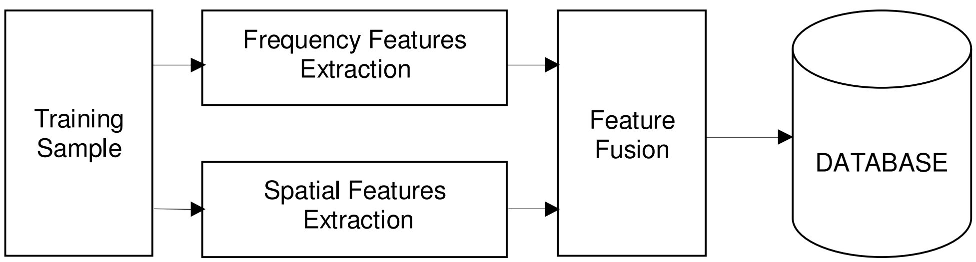


FIGURE 4: Learning stage of the proposed gender classification system

The learning algorithm is as follows:

Learning Algorithm:
[Input] all samples of fingerprint with known class (Gender)
[Output] the feature vector of all samples as database

1) Decompose the fingerprint with 6 level decomposition of DWT.
2) Calculate the sub-band energy vector (E) using (1).
3) Calculate the Eigen vector (V) using (2).
4) Fuse the vectors E and V to form the feature vector for the particular fingerprint.
5) Insert this feature vector and the known class into the database.
6) Repeat the above steps for all the samples.

4.2. KNN Classifier

In pattern recognition, the k-nearest neighbour algorithm (K-NN) is the generally used method for classifying objects based on closest training examples in the feature space. K-NN is a type of instance-based learning where the function is only approximated locally and all computation is deferred until classification. In K-NN, an object is classified by a majority vote of its neighbours, with the object being assigned to the class most common amongst its k nearest neighbours (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of its nearest neighbour. The neighbours are taken from a set of objects for which the correct classification is known. This can be thought of as the training set for the algorithm, though no explicit training step is required.

4.3. Classification Stage

In the classification phase, the fused feature vector of the input fingerprint is compared with the feature vectors in the database by using the K-Nearest Neighbour classifier. The distance measure used in the classifier is 'Euclidean Distance'. The detailed classification algorithm is detailed below.

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 given unknown fingerprint with 6 level decomposition of DWT.
2) Calculate the sub-band energy vector (E) using (2).
3) Calculate the Eigen vector (V) using (1).
4) Fuse the vectors E and V to form the feature vector for the given unknown fingerprint.
5) Apply KNN classifier and find the class of the unknown fingerprint by using the database generated in the learning phase.

4. EXPERIMENTAL RESULTS

In this section, the performance of the proposed Age estimation algorithm is verified by using the internal database. The success rate (in percentage) of age classification using the combination of both DWT and SVD are summarized and discussed. DWT level 5, 6 and 7 were tried and from the results, DWT level 6 is identified as the optimum for the age estimation.

4.1. Data Set

The fingerprint images of internal database were collected by using Fingkey Hamster II scanner manufactured by Nitgen biometric solution [18], Korea. Every original image is of size 260x300 pixels with 256 grey levels and resolution of 500 dpi. The internal database includes all ten fingers of the subject scanned. The images are collected from males and females of different ages. From the internal database, irrespective of quality and age, all ten fingers of 3570 fingerprints in which 1980 were male fingerprints and 1590 were female fingerprints are used for testing and training. These 3570 fingerprint images are separated into two sets. For the learning stage 2/3 of total images are used. The remaining images are used in the classification stage. Table 1 shows the age and gender wise samples of the internal database. The crime rate recorded is high between the ages of 12 to 35. Below the age of 12 and above 36 the crime rate is few and thus large samples from 283 persons (156 male and 127 female) were used for testing the method. These samples are classified under the three groups as 13-19, 20-25 and 26-35. Each person's all fingers are scanned and frequency features were identified through DWT and spatial features were identified through SVD. Initially, KNN was applied for the feature set of DWT alone. Similarly, KNN was applied for the feature set of SVD alone and the fused feature set of DWT and SVD.

Age Group	Male	Female	Total
Up to 12	70	60	130
13-19	190	320	510
20-25	1050	680	1730
26-35	320	270	590
36 and above	350	260	610
Total Samples	1980	1590	3570

TABLE 1: Age and gender wise samples details

All the fingers of a person are scanned to test the proposed algorithm. The proposed method is tested with all five fingers of the left and right hand. Thus to have the reference of the fingers, the scanned fingers were numbered as follows. Little finger to thumb fingers of left hand is numbered as 1 to 5. Thumb to little fingers of right hand is numbered as 6 to10 as shown in figure 5.

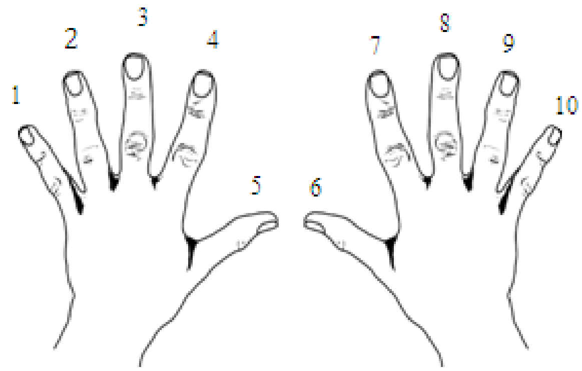


FIGURE 5: Finger numbering

4.1 Age Estimation

In table 2 the success rates (in percentage) of age estimation for the male fingerprints are tabulated. For the fingerprints of the male persons whose age lies below 12 years, the success rate is achieved with 96.67%.In this category, other than the left hand thumb, the age is estimated exactly for all fingers. The success rate in the age group of 20-25 is reasonably good (86.26%) and thus useful for crime investigation, as this group crime rate is higher than other groups. In addition, if there is availability of right thumb and right index finger, the success is nearly 90%. Similarly the success rate for the remaining group is achieved as 71.75%, 76.39% and 53.14% for the age groups of 13-19, 26-35 and 36 and above respectively. Maximum success rate is achieved in the age group of 'up to 12' for all fingers except the left thumb. Low success rate is recognized for the age group of '36 and above'.

Fingers	Age groups				
	up to 12	13-19	20-25	26-35	36 and above
1	100.00	72.22	80.81	75.00	51.43
2	100.00	84.21	83.84	72.22	51.43
3	100.00	72.22	86.87	69.44	54.29
4	100.00	66.67	83.84	83.33	51.43
5	66.67	66.67	88.89	72.22	51.43
6	100.00	77.78	89.90	80.56	54.29
7	100.00	72.22	83.84	80.56	51.43
8	100.00	66.67	87.88	69.44	57.14
9	100.00	72.22	89.90	80.56	54.29
10	100.00	66.67	86.87	80.56	54.29
Average	96.67	71.75	86.26	76.39	53.14

TABLE 2: Success rate (in percentage) of age estimation for the male fingerprints

Similar to the male age estimation, the success rates (in percentage) of age estimation for the female fingerprints are calculated. For the fingerprints of the female persons whose age lies below 12 years, the success rate is achieved with 66.67%. The success rate in the age group of 20-25 is reasonably good (76.77%) and thus useful for crime investigation, as this group crime rate is higher than other groups. In addition, if there is availability of right and left small fingers of female, the success is nearly 81%. Similarly the success rate for the remaining group is achieves as 63.64%, 72.41% and 16.79% for the age groups of 13-19 26-35 and above 36 respectively. Maximum success rate is recognized for the right little finger of the age group ’20-25’ and the lowest success rate are notices in the right ringer finger of the age group ’36 and above. Finger-wise age estimation success rate is tabulated in table 3.

Fingers	Age groups				
	up to 12	13-19	20-25	26-35	36 and above
1	66.67	63.64	80.00	68.97	17.86
2	66.67	63.64	76.92	75.86	14.29
3	66.67	63.64	78.46	68.97	17.86
4	66.67	63.64	72.31	72.41	14.29
5	66.67	63.64	78.46	75.86	17.86
6	66.67	63.64	73.85	72.41	14.29
7	66.67	63.64	72.31	72.41	21.43
8	66.67	63.64	76.92	68.97	21.43
9	66.67	63.64	76.92	72.41	10.71
10	66.67	63.64	81.54	75.86	17.86
Average	66.67	63.64	76.77	72.41	16.79

TABLE 3: Success rate (in percentage) of age estimation for the female fingerprints

Age group-wise average success rate for male and female is shown in the line diagram of figure 6. Maximum success rate of 96.67% is achieved for the age group of ‘up to 12’ years of male fingers and 76.77% is achieved for ’20-25’ age group for female fingers. For the age group of ‘36 and above’, the success rate is low and 53.14% and 16.79% for male and female fingers respectively.

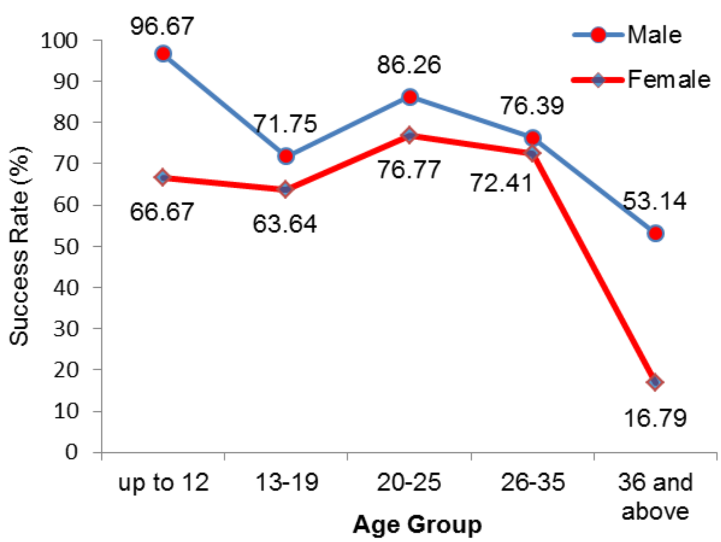
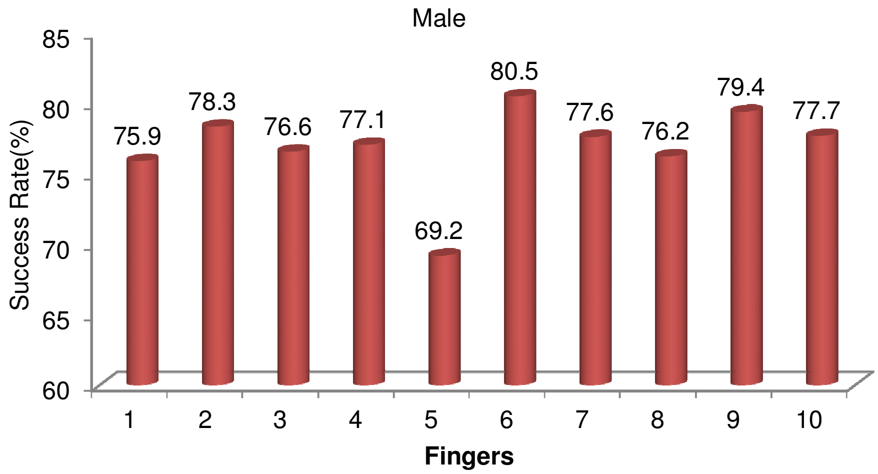
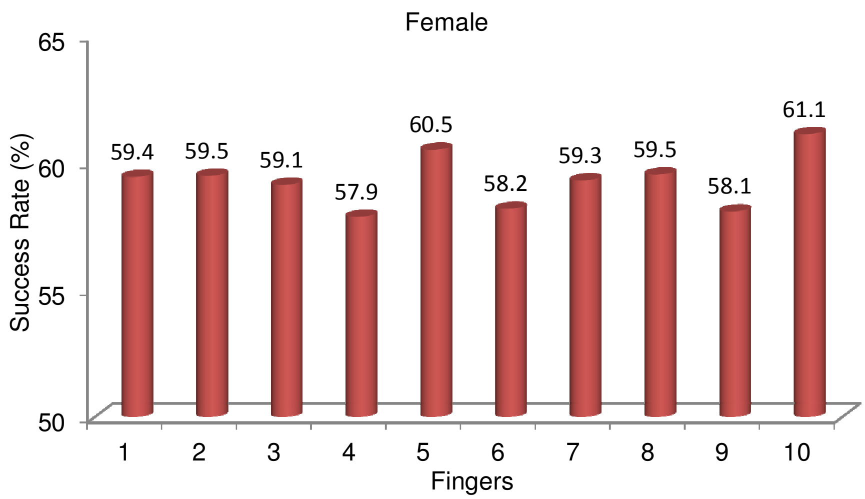


FIGURE 6: Age group-wise Average success rate

By average for any given fingers, 76.84% success rate is achieved for the male and 59.26% is achieved for the female fingers in all the five groups. Also, age estimation for the right and left hand are calculated. As discussed, left hand small finger to thumb fingers are named 1 to 5 and the right hand thumb finger to small finger are named 6 to 10. Average age estimation, for the left hand fingers among all the fingers are calculated as 75.41% for male and 59.28%. Similarly, 78.28% and 59.23% are the success rates for right hand fingers of male and female respectively among all groups. Finger-wise success rate for the male and female fingers are shown in figure 7(a) and 7(b) respectively.



(a)



(b)

FIGURE 7: Finger-wise success rate (a) Male (b) Female

5. CONCLUSIONS

In this work, we have proposed a new method of age estimation from fingerprint images based on level 6 DWT and SVD. The level 6 DWT is selected as optimum level by analysing the results obtained for other levels. DWT and SVD also applied to classify the fingerprints in to the five age groups. According to the crime reports of Canada and Indian police record, ages has been grouped as up to 12, 13-19, 20-25, 26-35 and above 35. Exact estimation of age group is achieved for the age group below 12 years. For the age group of 36 and above the success rate is not reasonably good.

Higher crime rate has been recorded in Canada and Indian police records in the ages, ranges 20 to 35 of both male and female. The proposed method gives age estimation rate of 81.33% and 74.59 for male and female respectively. If the right thumb and right ring fingers of male is given, the success rate is attained as 85.23% and 78.7% for female little fingers. The overall success rate is 76.84% for male and 59.26% for female. While testing the right hand male fingers alone, 78.28% of accurate estimation is attained. Similarly for the male, irrespective of right or left hand the success rate is 59.3%. More accuracy rate of age estimation can be achieved if more number of samples in each category is trained.

For better results of age estimation, authors are working in collecting huge samples in the each category is initiated. In addition, the research work has been extended using the spatial parameters of fingerprint. Moreover, it is aimed to use various other classifiers for the better results. In the proposed work five age groups has been made for the age estimation. In the future work, more groups will be made to find the age of the suspect or the person.

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