CHAPTER 1

INTRODUCTION

1.1 RESEARCH BACKGROUND

Biometrics system has become a part of every individual’s day-to-day life, being applied in areas as simple as physical access entry and as exhaustive as for criminal and civil applications. The market growth of the biometrics is mainly due to the increasing concerns of the countries in terms of strengthening national security. It is expected soon that the biometrics will become integrated within a wide number of mobile devices in the near future for fingerprint and gesture recognition functionality.

Accurate and automatic gender classification is needed in a wide range of applications like forensic anthropology, face recognition, demographics statistics, video surveillance, passive surveillance and control in smart buildings, gender mediated Human Computer Interaction (HCI) and collecting consumer statistics for advertisement and marketing. In forensic, gender and age information of an unknown body can guide the investigators to closely identify the person among a large number of possible matches. Many social functions/services critically depend on the correct gender and recognition of the gender boosts the performance of many applications.

In the crime scene investigations, body parts such as teeth, bones and other identifiable body parts of the human are being used for the gender and age identification. But the availability of such evidences is rare and thus it is difficult to detect exact gender. Remarkable study has been made in gender
identification using face biometrics but in the crime scene availability of face of the criminal is minimal. In the highly sophisticated investigations/situations as shown in Figure 1.1, gender and age classification have become essential requirements.

For classifying gender and estimating age, biometrics traits such as gait, iris, dental tissue, hand shape, speech, paralinguistic analysis, genetic features, etc., have been used. All these biometric approaches are unable to meet the needs of our sophisticated and well-connected electronic information society. In this work, fingerprint and ear have been used to correlate their various features with gender and age.
Fingerprint images have been widely used in personal identification, forensic applications, risk analysis, digital security and many other applications. Few researches were done and published in the aim of finding gender using fingerprint. The ear is considered an alternative biometric because of its unique features such as rich structure, small variations with age, gorgeous features which are not affected by facial expressions, etc. The advantage of using a human ear is its permanence with increase in age. “When you’re born your ear is fully formed. The lobe descends a little but overall it stays the same. It’s a great way to identify people,” say Nixon et al. (2010). Significantly, the appearance of the auricle (outer ear) is relatively unaffected by aging, making it better suited for identification when compared to other non-invasive techniques. Based on the variety of information available, the gender classification and age estimation have been processed using fingerprint and ear.

1.2 GENDER CLASSIFICATION USING FINGERPRINT

Traditional ridge-based sex determination used the inked fingerprints and manual measurements. The measurements of the parameters from inked fingerprint impressions (Dillon et al. 2001, Gungadin 2007, Nithin et al. 2011, Reddy 1975) result in poor gender classification rate. This technique was often imprecise because of poor ink print, smear and blurred fingerprints. Poorly maintained inking apparatus, fingers with foreign substances, partial fingerprints, smears and blurred fingerprint due to finger slip or twist while enrolling and poor cooperation of subject are the major causes of poor fingerprint impression. Also, the ridge thickness depends on the pressure applied and may provide false results on gender identification.

Ridges and their patterns exhibit a number of properties that reflect the biology of individuals. The fingerprint has about 150 possible ridge characteristics (Hong et al. 1998). Variations in ridge dimensions and sex
differences in ridge breadth have been reported (Cummins 1941, and Kralik and Novotny 2003). With the availability of latest computing technologies and robust classifiers, the analysis of ridges of fingerprint has become easier for any processing. Figure 1.2 shows a fingerprint with singular points (core and delta) and the popular ridge features of fingerprint.

![Fingerprint with features](image)

**Figure 1.2 Fingerprint and its features**

In existing methods of gender identification, various classifiers and some threshold methods have been used. To alleviate the limitations of identifying gender from a fingerprint, OSA method is proposed in this work. By OSA method, optimal scores are assigned to the fingerprint ridge parameters (ridge count and ridge width) and fingertip size based on its frequency of occurrence. These scores are assigned individually for male and female for each feature and the total score obtained for each gender is compared and the gender with greater score is declared as a result.
1.3 GENDER CLASSIFICATION USING EARPRINT

The structure of the ear has become popular, as it has a definite structure just like the face. The shape of the ear tends to be dominated by the outer rim or helix, and also by the shape of the lobe. In addition to the conspicuous rim or the helix, the ear also has other prominent features such as the anti-helix which runs parallel to the helix, and a distinctive hairpin-bend shape just above the lobe called the intertragic notch. The inner helix and the lower of these two branches form the top and left side of the concha, named for its shell-like appearance. Figure 1.3 shows a typical ear image with its standard features and some types of earprint.

(a) Ear image with its standard features

(i) Triangular     (ii) Round     (iii) Oval   (iv) Rectangular

(b) Types of earprints

Figure 1.3 Ear image with standard features and types of earprints
Earprint finds vital role in the persona identification. It is capable of identifying a subject at par with face recognition. Thus, as an additional approach, in this work, gender classification using earprint is also carried out. Three types of classifiers are used to determine the gender.

1.4 AGE ESTIMATION USING FINGERPRINT

Age information is important to provide investigative leads for finding unknown persons. Existing methods 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. Only a few works concentrated on the age estimation using the fingerprint. Thus in this work, using a fingerprint, age of a person has been categorized into any one of the four groups. The groups are 8-12, 13-18, 19-25, 25 and above.

1.5 CHALLENGES IN FINGERPRINT AND EAR ANALYSIS

The gender classification and age estimation involves several stages that include data acquisition, pre-processing, feature extraction, classifiers, identifying suitable methods to obtain best results. Suitable scanners and appropriate setting is required for the acquisition of biometric images. Pre-processing of the images needs to be done to improve the quality of the images which were taken at different ambience. Also the quality of the sample depends on the subject’s age, nature of his/her job, genetic nature and the region he belongs to. The challenges in fingerprint analysis and ear analysis for the achievement of the goal are explained below.

1.5.1 Challenges in Fingerprint Analysis

Many challenges need to be faced while finding the gender and age of a person based on the fingerprint features. The robustness of the proposed
system relies on the genuineness of the fingerprint features extracted which in turn depends on various factors. In the crime investigation, available latent fingerprint at the crime scene may be partial and affected with the pressure, surface variations and other variables. While acquiring the image using various sensors, noise on images affect the features. Placement of the finger on the sensor, cuts and bruises on the finger and finger pressure differences cause different impressions of the fingerprint to appear different. As in this work, the ridge details are collected with respect to the core and delta points of the fingerprint, during the sample acquisition, care must be taken, so that both core and delta points are present. In addition, depending on the type of the fingerprint, selecting the core and delta points needs to be identified. For example, the whorl type fingerprint has two core and two delta points and the plain arch not having the delta and core points. Thus utmost care should be taken to choose the points. By manual selection of these points, the results will be far better than the automatic identification of singular points.

Another major challenge is the pressure applied on the finger. The amount of pressure applied to a finger will affect the ridge edge features. Changes in the edge features also are affected by other variables such as surface variations and latent composition. The amount of deposition pressure is visible in a developed latent or inked fingerprint by the flattening or broadening of the ridges. The amount of deposition pressure is visible in a developed latent or inked fingerprint by the flattening or broadening of the ridges. A light touch shows only the top of the friction ridges and the impression is light in a lighter impression. The development may occur on the higher ridges, but not in the valleys or lower tapering ridge endings. In a lighter impression, the development may occur on the higher ridges, but not in the valleys or lower tapering ridge endings. A medium touch flattens the ridges more and is ideal for third level detail and clarity. A medium amount of pressure (between two and seven kilograms) is ideal when comparing fingerprints.
1.5.2 Challenges in Earprint Analysis

The first and foremost challenge in ear biometric is the image acquisition. It needs well defined lightings and good cooperation of the subject in order to acquire an acceptable ear image for registration. This requirement imposes a restriction on the use of ear biometrics in non-cooperative scenarios. Otherwise, a robust capturing system needs to be developed, for acquiring earprints of a subject from a distance while he/she is engaged in other activities.

In the absence of a well-controlled environment, illumination dramatically affects the image acquisition attempts. The auricle may cast shadows on other parts of the ear, which in itself is a kind of occlusion. A small degree of head rotation may cause a significant displacement in the captured ear image. Complex algorithm is required for cropping the ear from the image of the head.

Hair and jewel occlusion on the earprint needs to be removed while applying machine learning techniques. A blurred photograph or the photograph taken at the poor lightings and bright lightings may not be useful for the analysis even with sophisticated pre-processing techniques. A standard procedure needs to be followed to crop the ear image from the side face. In addition depending on the application more challenges need to be addressed.

1.6 STATE-OF-THE-ART IN GENDER CLASSIFICATION

A number of systems exist for gender classification using fingerprint features. Even though there are many publicly available databases, they are much concentrated in the area of authentication and thus provide performance evaluation and bench mark for fingerprint verification and classification. In addition, the publicly available databases do not contain the
gender details and the age. It was only mentioned the range of ages of the volunteers who gave the samples. Also, some of the databases contain the inked fingerprint samples and they have done the experiments manually. Table 1.1 lists some of the publicly available fingerprint databases. More details on the scanners used, volunteers who gave the samples, purpose of collecting samples etc., could be obtained from the website mentioned.

**Table 1.1 Few publicly available fingerprint databases**

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Male</th>
<th>Female</th>
<th>Samples taken</th>
<th>No. of Samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>SDUMLA-HMT (<a href="http://mla.sdu.edu.cn/sdumla-hmt.html">http://mla.sdu.edu.cn/sdumla-hmt.html</a>)</td>
<td>61</td>
<td>45</td>
<td>Thumb, index and middle finger of both hands</td>
<td>530</td>
</tr>
<tr>
<td>BioSecure datasets (<a href="http://atvs.ii.uam.es/databases.jsp">http://atvs.ii.uam.es/databases.jsp</a>)</td>
<td>2</td>
<td>2</td>
<td>Thumb, index &amp; middle finger of both hands</td>
<td>144</td>
</tr>
<tr>
<td>MCYT Database (<a href="http://www.infor.uva.es/biometria">http://www.infor.uva.es/biometria</a>)</td>
<td>NA</td>
<td>NA</td>
<td>All fingers (12 samples of each finger)</td>
<td>39600</td>
</tr>
<tr>
<td>FVC2006 (<a href="http://bias.csr.unibo.it/fvc2006/databases.asp">http://bias.csr.unibo.it/fvc2006/databases.asp</a>)</td>
<td>NA</td>
<td>NA</td>
<td>Index and middle fingers of both hand</td>
<td>1800</td>
</tr>
<tr>
<td>FVC2004 (<a href="http://bias.csr.unibo.it/fvc2004/">http://bias.csr.unibo.it/fvc2004/</a>)</td>
<td>NA</td>
<td>NA</td>
<td>Index and middle fingers of both hand</td>
<td>3520</td>
</tr>
</tbody>
</table>

There are many ear databases available as licenced or freely downloadable. Popular databases are USTB databases, UND databases, WPUT-DB, IIT Delhi, IIT Kanpur, ScFace, YSU, NCKU and UBEAR dataset. The details of ear databases are summarized by Pflug and Busch (2012). Many research articles report results on their proprietary databases and, therefore, their results cannot be independently verified and compared. Thus, the state-of-the-art gender classification has not met on any public domain database. However, the results declared by Badawi et al. (2006) and Verma and Agarwal (2008) are compared with our results.
1.7 RESEARCH OBJECTIVES

The main goal of this work is to analyse various fingerprint features and to classify whether the given fingerprint is male or female. In addition, earprint has been analysed to identify the gender and using fingerprint, age of a subject has been categorized by his/her fingerprint. The fingerprint features extracted are supposed to provide an easy way to recognize and analyze a fingerprint in different applications. These findings will also assist as a predictive parameter in forensic science and crime investigation.

1.8 OUTLINE OF THE THESIS

The thesis report is organized as follows. Chapter 2 summarizes related works and details the motivations for this research work based the previous works. Chapter 3 discusses three methods of fingerprint feature extraction and they are briefed below.

1. Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT) and Power Spectral Density (PSD) of the fingerprints were computed. From the transforms, the fundamental coefficients (the first elements of the coefficient matrix) were chosen as frequency domain features.

2. The output of Discrete Wavelet transforms (DWT) was used as a frequency domain features and the output of Singular Value Decomposition (SVD) was used as spatial features of fingerprint. Both features were concatenated and used as feature vector.

3. In the third approach, the parameters of Ridge Count (RC) and Ridge Width (RW) besides the Fingertip Size (FS) of the fingerprint were used as spatial features.
Chapter 4 discusses feature extraction from ear. For ear feature extraction, the earhole was considered as reference point and Euclidean distance was measured between the identified ear features and the ear hole. The ear features considered were outer lobe edge, outer and inner curves of the helix, outer and inner curves of the antihelix and two edges of the concha.

Chapter 5 describes the way of finding gender classification using fingerprint features. The Fundamental Coefficients (FC) or the DC coefficient (for the entire array) obtained through FFT, DCT and PSD were compared to set threshold for gender classification. The feature vector $V$ of size 1x260 obtained by SVD and the sub band energy vector $E_k$ of size 1x19 obtained by DWT level 6 were concatenated to form the feature vector. This feature vector with K-Nearest Neighbour (KNN) classifier was used for gender classification. A novel method of Optimal Score Assignment (OSA) is proposed for gender classification based on the frequency of occurrence of ridge width, ridge counts and fingertip size.

Chapter 6 presents the gender classification using earprint and its results. Euclidean distances were measured between ear hole and various standard features were taken as features. KNN, Bayes, and NN classifiers were used for gender classification.

Human age estimation using fingerprint was proposed in the Chapter 7. The features from DWT and SVD were used for age estimation. The age was categorized in to one of the four groups. The groups were 8-12, 13-18, 19-25, 25 and above.

Chapter 8 presents the salient findings identified from the fingerprint and earprint features and the gender classification and age estimation results achieved. Suggestions for future work are also discussed.