Chapter - 1

Introduction

1.0 Background

The Iris is completely formed by 8th month of foetus, and remains stable throughout the life. Statistically more accurate than the DNA matching since the probability of 2 irises being identical is 1 in $10^{78}$ persons [Daug07]. Iris is unique and the best biometrics that is mainly used for the establishment of instant personal identity [Kuma10]. The iris recognition based Personal Identification System has drawn much attention due to its convenience and security. In the battle of copyright piracy, the watermark is nowadays used in conjunction with several biometrics including fingerprint [Jain00], face [Tzou05], voice [Lee05a], retina [Coat05], signature [Maio07] and hand [Jain08]. The secure template storage techniques [Vetr09], [Sant10] were introduced in the iris recognition systems to make the system more secure. Approaches to generate cryptographic keys out of biometric measurements have been proposed in [Bodo94], [Rath07]. Further, the biometric authentication [Jain07] is useful for continuous authentication and several studies on this topic have been performed [Monr00], [Alti03], [Kang06], [Sim07], [Azzi08]. Also, the soft biometric traits [Jain04], [Jain04a] like gender, skin color, and hair color are more useful in identifying the individuals.

1.1 Biometrics

Biometrics has become a very popular topic and gained high interest from the researcher for the past two decades. Biometrics refers to the identification and verification of a human identity by measuring and analysing the physiological or the biological information of a human. The term biometrics comes from Greek words bios and metron gives the
meaning of life measurement. Most security professionals choose biometrics to be the best method for the identification and authentication purpose because biometrics comes from the nature and it is the determination of who you are?. The uniqueness of biometrics is an undeniable reality known by all.

A biometric system provides automatic recognition of an individual based on some sort of unique features or characteristics possessed by the individual. Biometric systems have been developed based on fingerprints [Malt03], facial features [Chel95], voice [Camp97], hand geometry [Ross99], handwriting [Nalw97] and the one presented in the thesis, the iris. Biometric systems work by capturing a sample of the features, such as taking a digital color image for face recognition etc. The sample is then transformed using some sort of mathematical functions into a biometric template. The biometric template will provide a normalized, efficient and highly discriminating representation of the features, which can then be objectively compared with other templates in order to determine the identity of a person. Most biometric systems allow two modes of operation: (i) an enrolment mode for adding templates to a database; (ii) an identification mode, where a template is created for an individual and then a matching is performed with the database of pre-enrolled templates.

A good biometric is highly unique, stable, be easily captured, and prevent misrepresentation of the features. There are lesser possibilities for two people having same characteristics which do not change over the time. Primary biometrics and soft biometrics are the two major categories available widely. Primary biometrics traits can be divided into two categories based upon the underlying characteristics namely physiological and behavioural. Physiological biometrics uses the characteristics based upon physical aspects of the body, such as a fingerprint, face, iris and retina. Behavioural biometrics utilises the unique way in which human characterises and authenticates persons, such as the way in which they speak, type and sign their name.
The categories of soft biometric traits are physical, behavioural or adhered human characteristics. These categories are established and time-proven by humans with the aim of differentiating individuals. In other words the soft biometric trait instances are created in a natural way, used by humans to distinguish their peers. Traits which accept the above definition include, but are not limited to: physical (skin color, eye color, hair color, presence of beard, presence of moustache, height and weight), behavioural (gait and keystroke) and adhered human characteristics (clothes color, tattoos and accessories). Soft biometrics inherits a main part of the advantages of biometrics and furthermore endorses by its own assets. Some of the advantages include non-obtrusiveness, computational and time efficiency, and human compliance. Furthermore, they do not require enrolment, nor the consent or the cooperation of the observed subject.

1.2 Comparison of biometrics

1.2.1 Primary Biometrics

The accuracy, performance, usability, measurements, speed, cost and privacy are the parameters mainly considered to compare primary biometrics. Accuracy indicates how accurately the technology measures the individual’s identification. Usability indicates easy use of the system. Smallness indicates the size of the capturing device. Spoof proof indicates how easy it is to fool the system and impersonate someone else. Speed indicates the length of time from beginning of operation until final authentication or identification. Privacy indicates the degree to which the system is perceived as intruding into the person’s privacy. Low cost indicates total cost of the system and its implementation. Universality indicates the degree to which the specific trait being measured is present in everyone. A comparison of some primary biometrics in terms of above mentioned parameters are given in Table 1.1.
Table 1.1 Primary biometrics comparison

<table>
<thead>
<tr>
<th>Biometrics</th>
<th>Accuracy</th>
<th>Usability</th>
<th>Smallness</th>
<th>Spoof proof</th>
<th>Speed</th>
<th>Privacy</th>
<th>Low cost</th>
<th>Universality</th>
</tr>
</thead>
</table>

- Excellent
- Good
- Fair
- Poor

### 1.2.2 Soft Biometrics

Soft biometrics have gained more and more interest in biometry and other communities for various reasons, like the need for higher reliability in biometric systems and the great number of advantages coming along with the integration of soft biometric traits in systems. In this Chapter, an overview of soft biometric traits and their classification are presented.

A set of characteristics listed in Table 1.2, adhere the properties of the soft biometric traits. The set of soft biometric traits are not limited, with the advent of the advanced techniques in security system, there are many possibilities for the evolution of these traits. In order to distinguish the soft biometric traits, at preliminary stage, the biometric traits are identified according to the affiliation to *face* or *body* or *accessory* like clothes color and
glasses. In the context of biometrics security systems, though the classical *accessories* are not belonging to biometry, the existing systems adopt them in the category of soft biometrics. A further argumentation can be the intuitive human use of obvious accessory items as a means of description and discrimination, for example *the person in the red shirt*. Further significant factors for classifying soft biometric traits are *distinctiveness* and *permanence*. *Distinctiveness* is the strength with which a trait is able to distinguish individuals. Beard as an example has a low *distinctiveness*, since it can only be applied to the male part of the population and furthermore has binary categories. The *permanence* indicates a certain level of correlation between *distinctiveness* and *nature of value* such as continuous, discrete and binary. Continuous traits are in general more distinctive than discrete and moreover binary ones. In this context it needs to mention the difference between *nature of value* and human labelling of traits. While hair color has different nuances and is thus of continuous character, humans tend to label it for convenience purpose as discrete. This approach will as well be followed by soft biometrics estimation and detection algorithms, for example hair color in categories (black, blond, brown, etc.,) rather than RGB values.

The *permanence* of a trait plays a major role for the employable application. As an example an application, where identification within a day is required, will accept low permanent traits like age, weight or clothes color. The final subdivision *subjective perception* stands for the ability of humans to unambiguously identify specific soft biometric traits. Again, the *nature of value* plays an important part, since characteristics with binary categories, are generally more straightforward to be sensed than continuous ones. Increased subjective perception of discrete or continuous traits is further due to the not well-defined categories or the beholder’s percipience. In fact, the notion of soft biometrics bears subjectivity even in the decision of the nature of value. In other words, colors can be argued to be continuous, due to the huge variance in nuances blending into each other or discrete due
to the fact that colors can be described with discrete RGB values. It may be noted that the classification of soft biometric traits can be expanded, and some other aspects like accuracy and importance can be evaluated or deduced, depending on the cause of specification (e.g., suitability for a specific application).

**Table 1.2 Soft biometrics comparison**

<table>
<thead>
<tr>
<th>Soft biometric trait</th>
<th>Face/Body/Accessory</th>
<th>Nature of value</th>
<th>Permanence</th>
<th>Distinctiveness</th>
<th>Subjective perception</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skin color</td>
<td>Face</td>
<td>Continuous</td>
<td>Medium</td>
<td>Low</td>
<td>Medium</td>
</tr>
<tr>
<td>Hair color</td>
<td>Face</td>
<td>Continuous</td>
<td>Medium</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>Eye color</td>
<td>Face</td>
<td>Continuous</td>
<td>High</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>Beard</td>
<td>Face</td>
<td>Binary</td>
<td>Low/Medium</td>
<td>Low</td>
<td>Medium</td>
</tr>
<tr>
<td>Moustache</td>
<td>Face</td>
<td>Binary</td>
<td>Low/Medium</td>
<td>Low</td>
<td>Medium</td>
</tr>
<tr>
<td>Facial measurements</td>
<td>Face</td>
<td>Continuous</td>
<td>High</td>
<td>Medium</td>
<td>Medium/High</td>
</tr>
<tr>
<td>Facial shapes</td>
<td>Face</td>
<td>Discrete</td>
<td>High</td>
<td>High</td>
<td>High</td>
</tr>
</tbody>
</table>
| Facial feature
  measurements | Face                | Continuous      | High       | High            | Medium/High          |
| Facial feature
  shapes             | Face                | Discrete        | High       | High            | High                 |
<p>| Ethnicity             | Face                | Discrete        | High       | Medium          | Medium               |</p>
<table>
<thead>
<tr>
<th>Soft biometric trait</th>
<th>Face/Body/Accessory</th>
<th>Nature of value</th>
<th>Permanence</th>
<th>Distinctiveness</th>
<th>Subjective perception</th>
</tr>
</thead>
<tbody>
<tr>
<td>Marks</td>
<td>Face/Body</td>
<td>Discrete</td>
<td>High</td>
<td>Medium/High</td>
<td>Low</td>
</tr>
<tr>
<td>Make-up</td>
<td>Face</td>
<td>Discrete</td>
<td>Low</td>
<td>Low</td>
<td>Medium</td>
</tr>
<tr>
<td>Age</td>
<td>Face/Body</td>
<td>Continuous</td>
<td>Low/Medium</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>Height</td>
<td>Body</td>
<td>Continuous</td>
<td>Medium/High</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>Weight</td>
<td>Body</td>
<td>Continuous</td>
<td>Low/Medium</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>Gait</td>
<td>Body</td>
<td>Continuous</td>
<td>Medium</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>Body measurements</td>
<td>Body</td>
<td>Continuous</td>
<td>Medium/High</td>
<td>Medium/High</td>
<td>Medium</td>
</tr>
<tr>
<td>Body shapes</td>
<td>Body</td>
<td>Discrete</td>
<td>Medium</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>Clothes color</td>
<td>Accessory</td>
<td>Discrete</td>
<td>Low</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>Glasses</td>
<td>Accessory</td>
<td>Binary</td>
<td>Low/Medium</td>
<td>Low</td>
<td>Low</td>
</tr>
</tbody>
</table>

Choice of biometrics should consider the following parameters pertaining to the defined operational requirements. The parameters are accuracy, environment e.g., fully deployed battlefield, ergonomics or user-friendly, stability and uniqueness of feature to be measured, security, size, safety, speeds of enrolment and recognition, non-intrusiveness, convenience, size of stored template, operational limitations e.g., finger and facial recognition through nuclear biological, chemical or chemical biological radiation clothing, requirement
ability to perform both identification and verification, credible scientific background research, human acceptance, and robustness. After the consideration of all afore-mentioned biometrics and the parameters discussed above, the iris is taken for the research work.

1.3 The human iris anatomy

The iris is the “colored ring of tissue around the pupil through which light enters the interior of the eye” [Oyst99]. The anatomy of the human iris is shown in Figure 1.1. Two muscles, the dilator and the sphincter muscles, control the size of the iris to adjust the amount of light entering the pupil. A layer which covers the iris and the pupil is known as cornea. The pupil region generally appears darker than the iris. However, the pupil may have specular highlights, and cataracts can lighten the pupil. The iris typically has a rich pattern of furrows, ridges, and pigment spots. The average diameter of the iris is 12 mm and the pupil size can vary from 10% to 80% of the iris diameter [Wolf76].

The iris is composed of several layers. Its posterior surface (epithelium layer) consists of heavily pigmented epithelial cells that make it light tight (i.e., impenetrable by light). There are two muscles which are anterior to epithelium layer that are cooperatively controlling the pupil. There are two more layers such as stromal layer, and anterior border layer, which play vital role in anatomy of the iris. The former consists of collagenous and connected tissue in arch-like structure, and is radially arranged corkscrew like blood vessels. The latter is the most anterior layer, which contains individual pigment cells called chromatophores and also it is denser compared to that of stromal layer.

The visual appearance of the iris is a direct result of its multi-layered structure. The anterior surface of the iris seems to be divided into a central pupillary zone and a surrounding ciliary zone. The color of the ciliary zone may change person to person [Oyst99]. The border of these two zones is termed the collarette; it appears as zigzag circumferential ridges,
because *anterior border layer* ends abruptly near the pupil. The *ciliary zone* contains many interlacing ridges due to the support of *stromal layer*. *Contractile* lines here are varied with the state of the pupil. Additional *meridional ridges* are formed by radiating vasculature.

![Diagram of iris structure](image)

(a) The structure of the iris seen in a transverse section

![Diagram of iris structure](image)

(b) The structure of the iris seen in a frontal sector

**Figure 1.1** Anatomy of the human iris

Other assorted variations in appearance owe to *crypts* (irregular atrophy of the border layer), *nevi* (small elevations of the border layer), and *freckles* (local collections of *chromataphores*). In contrast, the *pupillary zone* is relatively flat. However, it often shows radiating spoke-like processes and a *pigment frill* where the posterior layer’s heavily pigmented tissue shows at the pupil boundary. Finally, iris color results from the differential
absorption of light impinging on the pigmented cells in the anterior border layer. While there is little pigmentation in the anterior border layer, light reflects back from the posterior epithelium and is scattered as it passes through the stromal to yield a blue appearance. Progressive levels of anterior pigmentation lead to darker colored irises.

The minute details of the iris textures are believed to be determined randomly during the fetal development of the eye and not related to any genetic factors [Wolf76]. The iris textures differ from person to person and also differ in left and right eyes of the same person [Daug01]. The color of the iris can change as the amount of pigment in the iris increases during childhood. Nevertheless, for most of the human’s lifespan, the appearance of the iris is relatively constant.

1.4 Biometric pattern recognition

A biometric pattern recognition system is able to perform automated authentication of users depending on their primary biometrics (physical and behavioural characteristics) and/or soft biometrics (physical, behavioural or adhered human characteristics). Such a biometric system consists of several basic entities:

Biometric Sensor: The biometric sensor performs the data acquisition and the analog to digital conversion. The outputs of the biometric sensor are the raw biometric data. The sensor is used at the enrolment time of a user and every time a user needs to be authenticated.

Feature Extraction: In the feature extraction, the raw data are processed and analysed. The result of the feature extraction should be the most distinctive features for every user. Feature extraction is performed during the enrolment process as well as during an authentication.
Database: Almost in all biometric recognition systems, a database is required. This database is used either to store raw biometric features or a hash value of these. Sometimes, the database may store cryptographic keys, which are released when an authorized user represents biometric features to the system.

Matcher: The biometric matcher is responsible for the matching process which should be tolerant in some way but should not provide any security leakage. Matching is performed whenever a user needs to be authenticated.

The two basic processes of a biometric authentication system are the enrolment process and the authentication process [Viel06]. In the enrolment phase of a biometric authentication system, all users are registered with the system, and references are stored in the database of the system. On the other hand, the authentication process denotes the process of identity verification or determination. In the authentication process, the system performs a comparison between the presented biometrics and the stored references of the previously enrolled one.

Enrolment: In the enrolment process, as shown in Figure 1.2, a user’s biometric data is presented to the authentication system for the first time. This analog data need to be digitalized for further use depending on the biometric characteristic. The result of this analog-digital conversion is called as enrolment samples. These samples are pre-processed and then features are extracted. The extracted features are then stored in databases. In most biometric of the pattem recognition systems, several data acquisitions are performed during the enrolment of a single user. At the time of enrolment of the user, the system requires a set of biometric data, among them a group of data sampled from those biometric data that are homogeneous. A set of features namely mean and standard deviation etc., are extracted, which are treated as representative of the user, and stored as feature vector in the feature
database. The efficiency of the system is strengthened by considering the features extracted from sampled homogeneous biometric data.

![Figure 1.2](image1.2.png)

*Figure 1.2* Enrolment process of biometric pattern recognition system

*Authentication:* After a user has been enrolled, the biometric pattern recognition system should be able to authenticate the user. At the time of authentication, the biometric data is presented to the system and digitalized. The obtained data, so-called *verification samples*, which are of the same as the raw data of the enrolment samples, and are pre-processed, then features are extracted. The matching process is performed by comparing the derived features with the features in the feature database. If the matching succeeds, then the user is authorized; otherwise the user is not permitted. This entire authentication process is illustrated in Figure 1.3.

![Figure 1.3](image1.3.png)

*Figure 1.3* Authentication process of biometric pattern recognition system
Verification and Identification: There are two modes verification and identification [Viel06], in which a biometric pattern recognition system is operated. In the first mode, a one-to-one comparison is performed by the biometric pattern recognition system. In the second mode, a one-to-many comparison is performed to identify the user. Furthermore, the process of identification is modelled as sequences of one-to-all verification. Therefore, the fundamental underlying mechanism is always verification.

Performance Measurement: Due to the fuzziness of the matching process of biometric pattern recognition systems, several errors occur. In generic biometric verification systems, there are two main types of errors: misrecognizing measurements of two different persons to be of the same person, called false acceptance and misrecognizing measurements of the same person to be of two different persons, called false rejection. The performance of a biometric pattern recognition system is commonly described by its False Acceptance Rate (FAR) and False Rejection Rate (FRR). The FAR and FRR are commonly accepted and quoted in almost all literatures concerning biometric pattern recognition systems. These two measurements can be controlled by adjusting a threshold, but it is not possible to exploit this threshold by simultaneously reducing FAR and FRR [Kong06]. Both have to be traded-off, as reducing FAR increases FRR and vice versa. For example, if an authentication scheme tends to be tolerant with respect to accepting similar biometric data, the FAR of this system will be very high while the FRR would be satisfying. Another important performance index of a biometric pattern recognition system is its Equal Error Rate (EER) defined as the point where FAR and FRR are equal. A perfect system in terms of accuracy would provide an EER of zero. Beyond that, there are some other commonly used measures for technical evaluation of a biometric system such as false match rate, false non-match rate, receiver operating characteristic, failure to acquire rate and the failure to enroll rate. In Table 1.3, these evaluations are summarized and explained.
Table 1.3 Overview of the most common evaluations in biometric pattern recognition systems

<table>
<thead>
<tr>
<th>Measure</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Failure to Acquire Rate</td>
<td>Ratio between number of biometric samples which could not be correctly acquired due to some reasons and total number of acquisitions</td>
</tr>
<tr>
<td>Failure to Enroll Rate</td>
<td>Ratio between the number of users who could not be enrolled correctly due to some reason and the total number of users</td>
</tr>
<tr>
<td>False Acceptance Rate (FAR)</td>
<td>Ratio between the number of truly non-matching samples which are matched by the system and the total number of tests including first two rates</td>
</tr>
<tr>
<td>False Rejection Rate (FRR)</td>
<td>Ratio of the number of truly matching samples which are not matched by the system and the total number of tests including first two rates</td>
</tr>
<tr>
<td>Equal Error Rate (EER)</td>
<td>The point on the error rate diagrams where FAR and FRR are equivalent</td>
</tr>
<tr>
<td>False Match Rate (FMR)</td>
<td>Ratio between the number of truly non-matching samples which are matched by the system and the total number of tests</td>
</tr>
<tr>
<td>False Non-Match Rate (FNMR)</td>
<td>Ratio of the number of truly matching samples which are not matched by the system and the total number of tests</td>
</tr>
<tr>
<td>Receiver Operating Characteristic (ROC)</td>
<td>The diagram of a verification system where the FMR and the FNMR are specified as the x-axis and y-axis</td>
</tr>
</tbody>
</table>
Rest of this Chapter outlines the work pertinent to both soft biometrics and primary biometrics recognition. This overview does not claim to be an exhaustive state of the art, but rather a highlight selection on performed scientific studies.

1.4.1 Facial Soft Biometric Recognition

It is observed from the literature that most of the works concentrate on soft biometrics have been performed predominantly with the aim of pre-processing. In face recognition for person identification, for instance, beard detection and removal serves an improvement of recognition results, disregarding the information of the presence of beard.

*Color Based Facial Soft Biometrics*: The color based facial soft biometric traits (eye, skin, and hair color) are the most obvious facial identifiers, as mentioned primarily by humans when portraying unknown individuals. Challenges for skin classification are on the one hand the low spread of different skin colors in color space and on the other hand the high illumination dependence on classification. The latter is described in various skin locus literatures [Hadi02].

Hair color is detected by similar techniques like skin color and often researched along, but it has more broadly scattered color categories. In [Sun02], a method for human head detection based on hair color is proposed through the use of Gaussian mixture density models describing the distribution of hair color. In [Gutt00], the fuzzy theory is used to detect faces in color images, where two fuzzy models describe the skin color and hair color.

Eye color detection, unlike the other color based facial soft biometrics, is a relatively new research topic. Few literatures offer insight [Dant11], probably due to the fact that 90% of humans possess brown eyes. An advantage of eye color detection is the availability of all necessary information in images used for iris pattern analysis, and in fact, iris color is a free
side effect. Work on fusion between iris texture and color can be found in [Zewa04], where the authors fuse iris and iris color with fingerprint and provide performance improvement with respect to the unimodal systems. In [Puha08], iris color is used to successfully support an iris indexing method.

**Beard and Moustache Detection:** Presence of beard and moustache are not appearing in literature as an identification trait, but rather as an obstacle for face recognition, which is why their removal is performed as a pre-processing step. As an example, in [Kaus06], a beard removal algorithm from bearded images is shown using the concept of structural similarity and coordinate transformations.

**Age:** Age plays an important role for long time employable systems based on face or body and is a challenging and relatively new field. An interesting study on face changes over time can be found in [Patt07], which spans a biometric, forensic, and anthropologic review, and further discusses work on synthesizing images of aged faces. Weda and Barbieri [Wed07] proposed a technique, which distinguishes children from adults based on the face or iris size ratio. Viola-Jones face detection technique [Viol04] is used, followed by an iterative Canny edge detection and a modified circular Hough transform for iris measuring, with good results. In [Nken08], the authors observe facial skin regions of Caucasian women and build partial least square regression models to predict the chronological and the perceived age. They find out that the eye area and the skin color uniformity are the main attributes related to perceived age.

**Gender:** Gender perception and recognition has been immensely researched already in social and cognitive psychology work in the context of face recognition. From image processing point of view, the topic offers as well myriads of approaches. The latest efforts employ a selection of fused biometric traits to deduce gender information. For example, in
[Caif07] gait energy images and facial features are fused and classified by support vector machines. Saatci and Town [Saat06] proposed a technique, which combines gender and facial expression recognition system by modelling the face using an active appearance model, feature extraction using radial basis function and support vector machines for classification. The work in [Balu06] proposes using adaboost on several weak classifiers, applied on low resolution grey scale images yields good results. Matta et al. in [Matt08], present a novel multimodal gender recognition system, based on facial appearance, head and mouth motion, employing the means of a unified probabilistic framework.

Ethnicity: Ethnicity recognition is an ethically and sociologically hot debated trait, which also contributes to face recognition. In the context of ethnicity, a uniquely defined classification is a difficult but important task. For recognition of Asian and non-Asian faces in [Lu04], machine learning framework applies a Linear Discriminant Analysis (LDA) and multi-scale analysis. A further framework, integrating the LDA analysis for input face images at different scales, further improves the classification performance. Based on Gabor wavelet transformation [Hoso04], an ethnicity recognition approach is combined with retina sampling for key facial features extraction. Finally, support vector machines are used for ethnicity classification providing very good results, even in the presence of various lighting conditions.

Facial Measurements: Early on, the facial measurements were found as very distinctive and helpful in the context of facial recognition [Nixo85]. Subsequently, a number of research works contributes on 3-dimensional measurements of human face in different illuminations [Carn06]. Recent work on facial soft biometrics is performed on scars, marks and tattoos by the authors in [Lee08].
1.4.2 Body Soft Biometric Recognition

Height, gait, body weight and color of clothes concern the body and are the main traits that can be extracted from a distance. The best distinctiveness is provided by gait detection, so that gait occasionally is referred to as a primary biometrics.

*Gait:* Gait is a complex pattern that involves not only some anthropometric parameters but also behavioural information. It is one of the few traits that can be gathered at a distance. A preliminary experiment on gait analysis is presented in [Joha73], where the author uses lights attached to the joints of the human body to record subject’s gait models. The author demonstrates how observers can recognize walking of people familiar to them just by the light traces. Since 1970’s many authors were interested in the topic of automatic gait recognition. In [Wang03], a spatio-temporal signature is extracted by the moving silhouette, a principal component analysis is employed later to discard irrelevant information and finally supervised pattern classification techniques are performed in the lower dimensional Eigen space. For recognition with this analysis, both the structural and behavioural characteristics of gait are captured. Another interesting work is proposed in [Sama08], where gait is chosen as primary biometric trait to be coupled with semantic biometrics that seems to be a very similar concept to soft biometrics. The system merges the results of the signature generated by gait with the one generated by the semantic information in order to identify users of the biometric system. A recent approach based on soft biometrics is provided in [Mous10].

*Height:* For automatic height estimation, foreground and background recognition is necessary. It can be adopted by diverse silhouette extraction techniques used for gait recognition. Height is a trait employed for human tracking or as an aid for other algorithms, like gait. Important literatures in this context are [Crim00], [Madd05] and [Jege08], where single and multiple calibrated camera systems are used for height estimation, respectively.
The estimation is performed via the computation of height related to the real world coordinates estimated in camera images.

*Body Measures:* Work on anthropo measures was performed in [Chir02] and [Ben06] and involve height estimation and stride information [Chir02] or height estimation plus shoulder breadth [Ben06] for building up a multimodal identification system.

*Weight:* Only a few literatures on soft biometrics, which involve weight [Aili06], use a scale to weigh users of a fingerprint recognition system. By exploiting weight and body fat measurements the authors reduce the total error rate of the system by 2.4%. It is clear that weight represents a novel soft biometric trait that still has to be explored especially for what concerns its measurement.

1.4.3 Accessory Soft Biometric Recognition

The new soft biometrics definition allows the inclusion of accessories among these traits. Accessories can indeed be related to personal characteristics as sight problems in case of glasses or personal choices as adornment in case of jewellery.

*Eye Glasses Detection:* The foreunner for glasses detection are Jiang *et al.* in [Jian00], classically perform edge detection on a pre-processed gray level image. Certain face areas are observed and an indicator for glasses is searched. The most successful identifiable region for glasses is found to be the nose part of the glasses, between the eyes. A different approach for glasses extraction is employed in [Xiao04], where a face model is established based on the Delaunay triangulation. A 3D method to detect the frames of glasses is presented in [Wu02], where 3D features are obtained by a trinocular stereo vision system. Still now, the best results on glasses detection are achieved on thermal images [Heo04].
1.4.4 Fingerprint Recognition

To start with physiological characteristics, fingerprints are the oldest traits which have been used for more than a hundred years. In fingerprint authentication systems, mostly friction minutiae-based features are used while systems are rarely designed to use an entire image of a fingerprint [Malt03], [Rath03]. Therefore, the result of a common fingerprint authentication system’s data acquisition would be a set of minutiae points. These so-called minutiae are skin ridge impressions of fingers which only slightly change over time. These minutiae points serve as biometric features and are compared to each other in the matching process. This means there is a whole set of features which has to be compared to another set of features while it is not sure during the capturing of a person’s fingerprint the whole set of features is recorded or just a small subset due to bad quality of the fingerprint.

The main difficulty within fingerprint biometrics is the inability to somehow normalize fingerprint data, for example, by finding specific fingerprint orientation and its centre. If fingerprint data is not normalized, then all calculations resulting out of minutiae are destined to be orientation or position-dependent. The way to overcome this difficulty is to have the matching algorithm that deals with transformations of fingerprint data. Much work has been done to solve the problem of aligning fingerprint images including the use of high curvature points and orientation lines.

Another challenge is to deal with low quality images of fingerprints, in which the worst case is without distinct features (minutiae points) which are necessary for the matching process. Enabling a system to authenticate a person if only a subset of features is captured during the acquisition of the fingerprint is still a topic of research.
1.4.5 Face Recognition

In a face recognition system, images of the whole face of a person are captured out of which unique key features are extracted to identify person’s reliability [Turk91], [Chel95]. The acquired set of key features includes relative distances between characteristics such as eyes, the nose, the mouth cheekbones and the jaw. Using all of this information, a unique template is created by applying dimension reduction. For example, this is done by applying Eigenfaces [Turk91] in generic face recognition systems. This template may then be compared to databases of facial images to identify a person.

While a face recognition system has high acceptance, its accuracy is low [Mart05]. The problem arises mainly from three factors: insufficient capability of representing features in the feature space; within-class variations; between-class variations. Most of the face recognition systems are highly sensitive to variance of a person's face. Unfortunately, there is plenty of variation, for example, small movements of the head or changing haircuts. Thus, dimensionality reduction is performed to improve the capability to represent features and harmonizing the image taken.

1.4.6 Hand Geometry Recognition

Hand geometry is a biometrics that identifies users by the shape of their whole hand. For data acquisition, so-called hand geometry readers are used to measure a user's hand along many dimensions [Ross99], [Roy05]. These measurements serve as features which are used to authenticate a user by comparing these against previously stored ones. Since, hand geometry is not thought to be as unique and widespread as fingerprints, fingerprinting remains the preferred technology for high-security applications due to various forgery opportunities such as changing lengths of fingers with caps. Thus, it is advisable to use hand geometry combined with fingerprints to form a so-called two-factor authentication system.
1.4.7 Voice Recognition

One biometric characteristic which tends to be very difficult to handle is voice. On the one hand, voice biometrics is behavioural characteristic because it depends on the way a person talks (pronunciation, volume of speech). On the other hand, the voice can be seen as a physiological characteristic of a person as well. Data acquisition is first performed during the enrolment process where a person utters a password or passphrase to a device usually a microphone when prompted to do so. This signal is digitalized with an analog to digital converter and subsequently analysed resulting in a so-called voice model of a person [Camp97]. In the authentication process, the repeated utterance of the same password by the same person should authenticate a legitimate user. If a correct password is necessary the whole system is called token-based [Monr01]. Uttering an incorrect password the user will be rejected. Solving this difficulty voice authentication would offer many facilities. For example, a person could be identified during a phone call. However, a forger could still attempt to record a person to gain possession of a password. Voice is one human characteristic where the temporal order of the feature is important, which is typical behavioural biometric characteristic.

1.4.8 Signature Recognition

Speaking of signatures as a biometric characteristic of a person, one has to distinguish between so-called off-line and on-line signatures. Example for off-line signatures are the signatures on documents where nearly only spatial information such as features of curves can be analysed to identify a specific person, which is very unsatisfying. This is because off-line signatures refer to the result of a complete writing process. In other words, there is no information about the raw image of the signature. This image can be modified with the technique of dynamic time warping to correlate the result with other acquired off-line
signatures [Feng02]. Furthermore, shape-matching can be performed. On-line signatures are the signatures which are acquired using a palm or tablets. Therefore, access to signals during the writing process, so-called temporal information, is demanded [Nalw97], [Feng02], [Bum07]. This means, using on-line signatures, the physical activity of signing is measured and analysed. By doing so, many additional signals are offered which can be analysed to identify a person. These signals include the position of the pen, the time, the angle of the pen and the pen pressure. Additionally, the analog-digital conversion is performed. Some important features calculated out of these signals are the number of pen ups or downs, the average of absolute writing acceleration in y-direction, the effective average writing velocity in x-direction and the time the person takes to sign [Viel06]. Thus, there are plenty of features to analyse with on-line signatures.

1.4.9 Keystroke Dynamics

Keystroke dynamics is another behavioural biometric characteristic which could be additionally used to identify a person [Monr99]. For data acquisition the keyboard serves as biometric sensor with which two events (key down and key release) are measured. Every user develops a specific timing pattern when typing a password called keystroke dynamics. Duration and latencies of a user's keystroke dynamics are measured by the authentication system to enhance security. This means the correct password is necessary but does not suffice any more if the keystroke dynamics is measured as well. Very distinctive durations can be measured out of letters often following each other such as “th” in an English word for example. Problems occur within a system which uses keystroke dynamics as a biometric characteristic when keyboards are changed or if a user suffers from a hand injury. The approach of using keystroke dynamics is a simple example for combining the knowledge of something with a biometric characteristic.
1.4.10 Iris Pattern Recognition

Another physiological characteristic is a person’s iris, the sphincter around the pupil of a person’s eye. In the year 1885, a French ophthalmologist, Alphonse Bertillon first proposed iris pattern as a basis for personal identification [Bert85]. In 1987, Flom and Safir [Flom87] obtained an unimplemented concept of automated iris biometrics system. A theoretical study on iris pattern recognition [John92] was performed by Johnston and reported in 1992. In 1993, J. G. Daugman [Daug93] developed a technique to recognize iris patterns at the University of Cambridge Computer Laboratory, which is a breakthrough work of iris recognition. Further, he obtained the patent in 1994 [Daug94], and subsequently he proved the uniqueness of the iris patterns [Daug03] with the large iris database. It is also known as Daugman’s algorithm for which he holds key patent, which becomes the basis of all commercial iris recognition systems used today. Iris based security systems capture iris patterns of individuals and match these patterns against the records in available databases. Typical iris recognition system involves four main modules.

The first module, image acquisition, deals with capturing sequence of iris images from the subject using cameras and sensors. An image acquisition consists of illumination, position and physical capture system. Many iris recognition systems require stem cooperation of the user for image acquisition. Ketchantang [Ketc05] proposed a method in which the entire sequence of images is acquired during the enrolment and the best feasible images are selected to increase flexibility. The enrolment of the person aids to provide strong identity management. The occlusion, lighting, number of pixels on the iris are factors that affect the image quality [Bowy08].

The second module, pre-processing, involves various steps such as iris liveness detection, pupil and iris boundary detection, eyelid detection and removal, and normalization.
The iris liveness detection differentiates live subject from a photograph, a video playback, and a glass eye or other artifacts. There are very less possibility to forge the iris biometric features. Several methods like Hough transformation, integrodifferential operator, gradient based edge detection are used to localize the portions of iris and the pupil from the eye image. The contours of upper and lower eyelids are fitted using the parabolic arcs resulting the eyelid detection and removal. It is essential to map the extracted iris region to a normalized form. The iris localization methods are based on morphological operators [Mira03], spring force [He06], intensity gradient [Guo08]. Morphological operators were applied by Mira and Mayer [Mira03] to obtain iris boundaries by applying threshold, area opening and closing operators. The iris localization method developed by Zhaofeng He [He06] is based on spring force-driven iteration scheme using Hooke’s law. The composition of forces from all points determines the centre and radius of pupil and iris. The iris localization method by Guodong Guo [Guo08] is based on intensity gradient and texture difference. The intensity gradient method uses integrodifferential operator. The Kullback-Leibler divergence is used to measure the distance between two probability distributions derived from the inner and outer zones. H. Proenca and L. A. Alexandre [Proe05] proposed a moment-based texture segmentation algorithm, using second order geometric moments of the image as texture features. The experiments were conducted on a publicly available UBIRIS database [Proe05]. The segmentation performance for 1,214 good quality images and 663 noisy images is 98.02% and 97.88%, respectively. Furthermore, the clustering algorithms like self-organizing maps, k-means and fuzzy k-means are also used to segment the image, which produce the clusters-labeled images.

The third module, feature extraction, identifies the most prominent features for classification. Some of the features are x-y coordinates, radius, shape and size of the pupil, intensity values, orientation of the pupil ellipse and ratio between average intensity of two
pupils. These features are extracted using the methods based on phase [Daug93], texture [Wild94], zero-crossing [Bole98], independent component analysis [Huan02], local intensity variations [Ma03], etc. The features are encoded in a format suitable for recognition.

The fourth module, recognition, achieves result by comparison of features with stored patterns. Hamming distance [Daug93], normalized correlation [Wild94], and nearest centre classifier [Ma03] are the well-known methods used for matching purpose. The inter-class and intra-class variability are used as metrics for pattern classification problems.

1.5 Iris pattern recognition methods

1.5.1 Phase Based Methods

The phase based method recognizes iris patterns based on phase information. Phase information is independent of imaging contrast and illumination. Daugman designed [Daug93] and patented [Daug94] the first complete, commercially available phase-based iris recognition system in 1994. The eye images with resolution of 80 × 130 pixels iris radius were captured with image focus assessment performed in real time. The pupil and iris boundary are found using integrodifferential operator given in equation (1.1).

\[
\max_{(r, x_0, y_0)} \left| G_\sigma(r) \ast \frac{\partial}{\partial r} \int_{r, x_0, y_0} \frac{I(x, y)}{2\pi r} \, ds \right|
\]

(1.1)

where \( I(x, y) \) is the image in spatial coordinates, \( r \) is the radius, \( (x_0, y_0) \) is the centre coordinate, the symbol \( \ast \) denotes convolution and \( G_\sigma(r) \) is a Gaussian smoothing function of scale \( \sigma \). The centre coordinates and radius are estimated for both pupil and iris by determining the maximum partial derivative of the contour integral of the image along the circular arc. The eyelid boundaries are localized by changing the path of contour integration from circular to arcuate. The iris portion of the image \( I(x, y) \) is normalized to the polar form by the mapping function \( I(x(r, \theta), y(r, \theta)) \rightarrow I(r, \theta) \) where \( r \) lies on the unit interval \([0, 1]\)
and \( \theta \) is the angular quantity in the range \([0, 2\pi]\). The representation of iris texture is binary, which is coded by quantizing the phase response of a texture filter using quadrature 2D Gabor wavelets into four levels. Each pixel in the normalised iris pattern corresponds to two bits of data in the iris template. A total of 2,048 bits are calculated for the template, and an equal number of masking bits are generated to mask out corrupted regions within the iris. This creates a compact 256-bytes template, which allows for storage and comparison of iris.

The recognition in this method is the failure of a test of statistical independence involving degrees of freedom. Iris codes are different for different samples. The test is performed using boolean XOR operator applied to 2,048-bit phase vectors to encode any two iris patterns, masked by both of their corresponding mask bit vectors. From the resultant bit vector and mask bit vector, the dissimilarity measure between any two iris patterns is computed using Hamming Distance (HD) given in equation (1.2).

\[
\text{HD} = \frac{||(\text{code}_A \oplus \text{code}_B) \cap \text{mask}_A \cap \text{mask}_B||}{||\text{mask}_A \cap \text{mask}_B||}
\] (1.2)

where \( \text{code}_A, \text{code}_B \) are two phase code bit vectors and \( \text{mask}_A, \text{mask}_B \) are mask bit vectors. The \( \text{HD} \) is a fractional measure of dissimilarity with 0 representing a perfect match. A low normalized \( \text{HD} \) implies strong similarity of iris codes.

The methodology proposed by Martin Roche [Mart02] operates in the same concept of Daugman for recognition. In Martin’s method, the iris circumference parameters are obtained by maximising the average intensity differences of the five consecutive circumferences. The work by Xianchao Qui [Qui07] used 2D Gabor filters for localization. The filter response vectors were clustered using vector quantization algorithms like k-means. The experiments were conducted on CASIA-Biosecure iris database consisting of images captured from Asian and non-Asian race groups. The support vector machine was used for the two class ethnic classification.
Continuing the Daugman’s method, Karen Hollingsworth [Holl09] has developed many techniques for improving recognition rates. These techniques include fragile bit masking, signal-level fusion of iris images, and detecting local distortions in iris texture. The bits near the axes of the complex plane shift the filter response from one quadrant to adjacent quadrant in the presence of noise. In the fragile bit masking method, such bits called as the *fragile bits* are identified and masked to improve the accuracy. The signal-level fusion method uses image averaging of selected frames from a video clip of an iris. Local texture distortions occur with contact lenses with a logo, poor-fit contacts and edges of hard contact lenses, segmentation inaccuracies and shadows on the iris. These are detected by analysing iris code matching results. The $20 \times 240$ normalized images were covered with 92 windows each of size $8 \times 20$. Fractional HD was computed for each window. The location of windows with highest fractional HD was identified and removed from further calculations. The effect of dilation was studied by collecting datasets of images with varying degrees of dilation. The data was divided into subsets with small pupils, medium pupils and large pupils. The subset of data with large pupils showed worst performance with EER at an order of greater magnitude compared to that of small pupil data set.

### 1.5.2 Texture Analysis Based Methods

Wildes proposed iris recognition methods based on texture analysis [Wild94], [Wild96], [Wild97]. High quality iris images were captured using silicon intensified target camera coupled with a standard frame grabber and resolution of $512 \times 480$ pixels. The limbus and pupil are modelled with circular contours, which are extended to upper and lower eyelids with parabolic arcs. The particular contour parameter values $x, y$ and radius $r$ are obtained by the voting of the edge points using Hough transformation. The largest number of edge points represents the contour of the iris. The Laplacian of Gaussian (LoG) is applied to the image at
multiple scales and Laplacian pyramid is constructed. The LoG filter is given in equation (1.3).

$$-\frac{1}{\pi\sigma^4}\left(1 - \frac{\rho^2}{2\sigma^2}\right) e^{\rho^2/2\sigma^2} \quad (1.3)$$

where $\sigma$ is the standard deviation of the Gaussian and $\rho$ is the radial distance of a point from the filter’s centre. The matching is based on normalised correlation between the acquired and database images. Classification is performed using Fisher’s linear discriminant function.

The method for iris identification by Emine Krichen [Kric04] uses a hybrid method for iris segmentation, Hough transform for outer iris boundary and integrodifferential operator for inner iris boundary. The iris code is produced using wavelet packets. The whole image is analysed at different resolutions. 832 wavelets with 4 scales are used to generate 1,664-bit code. The iris database consists of 700 images acquired with visible light. An improvement of 2% FAR and 11.5% FRR was obtained relative to Daugman’s method. It was observed that by considering color information, overall improvement of 2% to 10% was obtained according to threshold values.

1.5.3 Zero-crossing Representation Method

The method developed by Boles [Bole98] represents features of the iris at different resolution levels based on the wavelet transform zero-crossing. The algorithm is translation, rotation and scale invariant. The input images are processed to obtain a set of ID signals and its zero-crossing representation based on its dyadic wavelet transform. The wavelet function is the first derivative of the cubic spline. The centre and diameter of the iris is calculated from the edge-detected image. The virtual circles are constructed from the centre and stored as circular buffers. The information extracted from any of the virtual circles is normalised to have same number of data points and a zero-crossing representation is generated. The
representation is periodic and independent from the starting point on iris virtual circles. These are stored in the database as iris signatures. The dissimilarity between the irises of the same eye images was smaller compared to the eye images of different eyes. The advantage of this function is that the amount of computation is reduced since the amount of zero-crossings is less than the number of data points. But the drawback is that it requires the compared representations to have the same number of zero-crossings at each resolution level.

1.5.4 Intensity Variations Method

Iris recognition system developed by Li Ma is characterized by local intensity variations [Ma03]. The sharp variation points of iris patterns are recorded as features. In the iris localization phase, the centre coordinates of the pupil are estimated by image projections in horizontal and vertical directions. The exact parameters of the pupil and iris circles are calculated using Canny edge detection operator and Hough transform. The iris in Cartesian coordinate system is projected into a doubly dimensionless pseudo-polar coordinate system. The local spatial patterns in an iris consist of frequency and orientation information. Gabor filters are constructed to acquire frequency band in the spatial domain. Gabor functions are Gaussians modulated by circularly symmetric sinusoidal functions. The feature extraction begins by generating 1D intensity signals considering the information density in the angular direction. The 1D signal is represented using dyadic wavelet transform to obtain the feature vector. It decomposes the signal into detail components at different scales. The feature values are the mean and the average absolute deviation of the magnitude of each $8 \times 8$ block in the filtered image with the total number of blocks being 768. For the dimensionality reduction and the classification, the Fisher linear discriminant analysis and nearest centre classifier are used respectively. The similarity between the pair of feature vectors is calculated using the XOR operation. The circular shift-based matching is performed from which the minimum matching score is considered after several circular shifts.
Alternatively, Li Ma proposed the orthogonal moment based method [Ma04] wherein the Gauss-Hermite moments of 1D signal are used as distinguishing features. These moments are effective to characterize the local details of the signal. Ten intensity signals were generated and four different order (1-4) moments were used. The feature vector was constructed by concatenating these features. The nearest centre classifier based on cosine similarity measure was adopted for classification in a low dimensional feature space. The method by Li Ma was further improved by Zhenan Sun [Sun05] wherein the local feature based classifier was combined with an iris blob matcher. The blob matching is aimed at finding the spatial correspondences between the blocks in the input image and that in the stored model. The similarity is based on the number of matched block pairs. The block attributes are recorded as centroid coordinates, area and second order central moments.

The method proposed by Jong Gook Ko [Ko07] is based on cumulative sum of change points. The iris segmentation uses Daugman’s method and the resultant segmented image is normalized to 64 × 300 pixel area. The feature extraction is performed using cumulative sums on groups of basic cells where each cell is of size 3 × 10. An average gray value represents the cell region for calculation. The cell regions are grouped horizontally and vertically and cumulative sums are calculated over each group. The iris feature codes are generated based on the sum in both horizontal and vertical directions. The maximum and minimum of the sum are calculated. For the summation values that lie between these two values: if the sum is on upward slope, the cell’s iris code is set to 1; if the sum is on the downward slope, the cell’s iris code is set to 2; otherwise cell’s iris code is set to zero. Matching is performed using Hamming distance.

Tajbakhsh [Tajb09] proposed region-based feature extraction method, which uses 2D discrete wavelet transform. The iris texture is partitioned into 32 × 32 pixel blocks and
then the 2D wavelet decomposition is performed on every block. The Gauss-Laguerre filter is used to generate a binary matrix, which is similar to iris code in Daugman’s method.

1.5.5 Independent Component Analysis Method

Ya Ping Huang [Huan02] developed an iris recognition system which extracts iris features based on Independent Component Analysis (ICA). The texture features are extracted from \( n \) number of samples taken from each concentric circle of the iris, and features are represented with \( m \times n \) matrix, where \( m \) is the number of concentric circles. Acquisition of the iris image is performed at different illumination and noise levels, and also proved that the system is robust for rotation and scaling. The independent components are uncorrelated, which are estimated and encoded using competitive learning mechanism based on kurtosis. The independent components are determined from the feature coefficients, which are non-Gaussian and mutually independent. The average Euclidean distance classifier is used to recognize the iris patterns.

1.5.6 Continuous Dynamic Programming Method

The technique proposed by Radhika [Radh09] recognizes the iris based on kinematic characteristics, and acceleration. The pupil extraction begins by identifying the highest peak from the histogram which provides the threshold for lower intensity values of the eye image. All the connected components in eye image with less than threshold intensity value are labeled. The pupil area of the eye is arrived by selecting the maximum area component. Normalised bounding rectangle is implemented using centre of pupil to crop iris. Continuous dynamic programming is used with the concept of comparing characteristics of the shapes in the iris. The acceleration plot is segmented and parts of acceleration curve are used to verify with the input’s acceleration curve. For iris, rate of change of gray level intensities within bounding box forms acceleration feature plot. The matching process is performed based on
the concept of accumulated minimum local distances between a reference template obtained using leave-one-out method and the input sample. The distance measure is the count of directional changes in acceleration plot. The local distances are directional changes in respective segmented slots of the acceleration plot.

1.6 Iris databases

There are presently 7 public and freely available iris image databases for biometric purpose. They are Chinese Academy of Sciences’ Institute of Automation (CASIA) [CASI06], Multimedia University (MMU) [Mult04], University of Bath (BATH) [Univ04], Palacký University Olomouc (UPOL) [Dobe04], Iris Challenge Evaluation (ICE) [Nati06], West Virginia University (WVU) [Ross04] and University of Beira Interior (UBIRIS) [Proe05]. The CASIA database is the most widely used in the iris research. However, its images incorporate few types of noise, almost exclusively related with eyelid and eyelash obstruction, similar to the images of the MMU and BATH databases.

The UPOL images are captured with an optometric framework, obtaining noise-free images with extremely similar characteristics. The ICE and WVU images contain several blurred and off-angle images. On the other hand, the UBIRIS database is built with the objective of simulating non-cooperative image capturing. This explains the higher heterogeneity of its images and the existence of large noisy regions like reflections and obstructions. Due to the space constraint, for sample, iris images with different features taken from various iris image databases are listed in Table 1.4.

1.7 Application systems

Major applications of iris pattern recognition so far have been: aviation security, and controlling access to restricted areas at airports; substitution for passports in automated international border crossing; database access and computer login; access to buildings and
<table>
<thead>
<tr>
<th>Database</th>
<th>Example image</th>
<th>Total image</th>
<th>Subjects</th>
<th>Image format</th>
<th>Resolution</th>
<th>Wave length</th>
<th>Varying distances</th>
<th>Acquisition device</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>CASIA.v1</td>
<td><img src="image" alt="CASIA.v1" /></td>
<td>756</td>
<td>108</td>
<td>BITMAP</td>
<td>320x280</td>
<td>Near infrared</td>
<td>No</td>
<td>CASIA camera</td>
<td>Previous filling of the pupil regions turns segmentation much more easier.</td>
</tr>
<tr>
<td>CASIA.v2</td>
<td><img src="image" alt="CASIA.v2" /></td>
<td>2400</td>
<td>60</td>
<td>BITMAP</td>
<td>640x480</td>
<td>Near infrared</td>
<td>No</td>
<td>CASIA camera</td>
<td>Subset of the subsequent database version.</td>
</tr>
<tr>
<td>CASIA.v3</td>
<td><img src="image" alt="CASIA.v3" /></td>
<td>22051</td>
<td>850</td>
<td>JPEG</td>
<td>640x480</td>
<td>Near infrared</td>
<td>No</td>
<td>OKI irispass-h</td>
<td>Images captured with two different devices. Contains images with close characteristic to the v1 version, with exception of the manual pupil filling.</td>
</tr>
<tr>
<td>CASIA.v4</td>
<td><img src="image" alt="CASIA.v4" /></td>
<td>54638</td>
<td>1800</td>
<td>JPEG</td>
<td>640x480</td>
<td>Near infrared</td>
<td>Yes</td>
<td>OKI irispass-h</td>
<td>Images captured with varying distance and close characteristic to v3 version.</td>
</tr>
<tr>
<td>MMU.1</td>
<td><img src="image" alt="MMU.1" /></td>
<td>450</td>
<td>384</td>
<td>BITMAP</td>
<td>320x280</td>
<td>Near infrared</td>
<td>No</td>
<td>LG EOC 2200</td>
<td>Noise factors avoided.</td>
</tr>
<tr>
<td>MMU.2</td>
<td><img src="image" alt="MMU.2" /></td>
<td>995</td>
<td>450</td>
<td>BITMAP</td>
<td>320x280</td>
<td>Near infrared</td>
<td>No</td>
<td>Panasonic BM-ET100US</td>
<td>Noise factors avoided.</td>
</tr>
<tr>
<td>UBIRIS.v1</td>
<td><img src="image" alt="UBIRIS.v1" /></td>
<td>1877</td>
<td>241</td>
<td>JPEG</td>
<td>200x150</td>
<td>Visible</td>
<td>No</td>
<td>Nikon E5700</td>
<td>Images captured under heterogeneous lighting environments. Several reflections and obstructions can be observed.</td>
</tr>
<tr>
<td>UBIRIS.v2</td>
<td><img src="image" alt="UBIRIS.v2" /></td>
<td>11102</td>
<td>261</td>
<td>TIFF</td>
<td>400x300</td>
<td>Visible</td>
<td>Yes</td>
<td>Canon EOS 5D</td>
<td>Details of the manually cropped resultant images.</td>
</tr>
<tr>
<td>UPOL</td>
<td><img src="image" alt="UPOL" /></td>
<td>384</td>
<td>64</td>
<td>PNG</td>
<td>567x768</td>
<td>Visible</td>
<td>No</td>
<td>SONY DXC-950P 3CCD with TOPCON TRC501A</td>
<td>Completely noise-free images acquired with an optometric framework under high constrained environment. Contains poor lighting, defocus blur, off-angle, and heavy occluded images.</td>
</tr>
<tr>
<td>WVU</td>
<td><img src="image" alt="WVU" /></td>
<td>3099</td>
<td>488</td>
<td>BITMAP</td>
<td>640x480</td>
<td>Near infrared</td>
<td>No</td>
<td>OKI irispass-h</td>
<td></td>
</tr>
</tbody>
</table>
homes; hospital settings, including mother-infant pairing in maternity wards; watch list database searching at border crossings; law enforcement at prison; secure access to bank accounts at cash machines; cell phone and other wireless-device-based authentication; biometric-key cryptography; automobile ignition and unlocking i.e., anti-theft devices; and government programmes such as birth certificates, entitlements and benefits authorisation.

Some of the deployed applications of iris pattern recognition are as follows: Negin et al. [Negi00] describe the sensor iris biometrics products such as a public-use system and a personal-use system for authentication applications; Pacut et al. [Pacu04] developed an iris biometrics system in Poland, which is envisioned to access the remote network; Jeong et al. [Jeon05] developed the iris recognition system in mobile phone only by using a built-in mega-pixel camera and software without additional hardware component; Schonberg and Kirovski [Scho06] described the EyeCert system, which issues identity cards to authorized users; In [Daug06], Daugman developed an iris recognition system to check visitors to the United Arab Emirates against a watch-list of persons who are denied entry to the country.

1.8 Challenging issues in iris pattern recognition

Even though significant progress has been made in iris recognition, handling noisy and degraded iris images require further investigation. The iris recognition algorithms need to be developed and investigated in diverse environment and configurations. The challenging research issues in iris pattern recognition are based on iris localization, non-linear normalization, occlusion, segmentation, imposter detection and large scale identification. Also, identifying the person with contact lens and removing the artifacts created by contact lens are challenging issues. Similarly, enrolling with contact lens and authenticating without contact lens, and vice versa are also challenging issues. Ultimately, developing the iris
recognition system with lowest false rejection rate and false acceptance rate with fastest composite time for template creation and matching is extremely challenging issue.

**1.9 Motivation of the proposed research work**

Benchmark in the field of iris pattern recognition is Daugman’s method, but this method requires 2,048 bits iris template and 2,048 bits mask to recognize the iris pattern and the use of integrodifferential operator to segment the iris consumes 329 msec, which is performed after the detection and removal of eyelids and eyelash of the eye. Later on, it is proved that the portion of iris itself is sufficient to recognize a person. So, there is a possibility in reduction of size of the code require to represent iris features and also reduction in segmentation time, thus the main motivation of the proposed research work is to design a novel technique based iris recognition for personal identification system with improved recognition accuracy, less computation and storage efficiency. Nevertheless, a number of research works have been performed on biometrics based digital copyrights, only limited number of literatures are available on iris based digital copyrights. Clearly, this indicates the lacuna in the image authentication. As there is a provision in reduction of the size of iris code and the invention of reversible watermarking techniques, hiding the iris code into the digital image for authentication motivated to develop the proposed research work.

Daugman’s method does not take care of the security of the iris code. Since the iris codes are stored in the storage media like hard disk and smart card, the loss of iris code is unacceptable. Storing the iris code as it is not the worthy solution. So, there is a necessity to transform the iris code into the irreversible form. To overcome the drawbacks in the existing system, the proposed work adopts the secure hash algorithm to make required transformation in the form of cancellable biometrics, which is more secured compared with existing system. Similarly, only few literatures that deal with biometric cryptography systems, since the
difficulty in handling the iris code fuzziness. This fuzziness can be solved by error correction codes used in the field of networks. The idea of solving the fuzziness of the iris code using low density parity check code becomes another motivation of the proposed research work. Particularly, evolving an innovative biometric cryptosystem by adopting networks concepts such as low density parity check codes, secure hash algorithm and advanced encryption standard schemes turn out to be the another motivation of the research work. Invention of dynamic authentication demands the continuous authentication with transparent and non-intrusiveness fashion. This can be achieved by monitoring the person continuously without interacting to the person concerned. The use of only primary biometrics for this purpose does not fulfill the requirement, since difficulty in capturing the primary biometrics continuously. The idea of integrating the temporal information i.e., soft biometrics such as color of the cloths, eye color, hair color and skin color, with the iris (non-orthogonal view) motivated to develop the proposed research work.

The objectives of the proposed research work

- To develop an iris pattern recognition algorithm with improved the recognition accuracy, computational and storage efficiency for a Personal Identification System.
- To improve the performance of iris pattern recognition using LDPC code for security applications, such as Image Authentication, Smart card Security, Biometric Cryptosystem.
- To modify the algorithm to recognize non-orthogonal iris for the color based facial and accessory soft biometrics integrated Continuous User Authentication System.

1.10 Organization of the thesis

The focus of the research work is to develop an iris pattern recognition algorithm and to improve the performance of iris pattern recognition using LDPC code for security
applications such as personal identification system, image authentication, smart card security, biometric cryptosystem and continuous user authentication. The rest of the thesis is organized as follows:

Chapter 2 discusses various stages of iris recognition such as segmentation (localization), normalization, feature extraction, code generation and matching. Canny edge detector and Hough transforms are used to improve the speed and accuracy of the segmentation process, which is explained in Section 2.2. Segmented iris is normalized using Daugman’s rubber sheet model in the ranges [-32°, 32°] and [148°, 212°] instead of the entire iris region, which is discussed in Section 2.3. The features are extracted by convolving the 1D signal with help of 1D Log-Gabor filter, Fast Fourier Transform (FFT) and inverse FFT, which is called phase data. This feature extraction process is described in Section 2.4. These features are encoded efficiently using phase quantization technique to produce a feature vector with discriminating texture features and a proper dimensionality to improve the recognition accuracy and computational efficiency. The details of code generation process are explained in Section 2.5. Section 2.6 elaborates the matching process based on Hamming distance. The experimental results are discussed in Section 2.7.

Chapter 3 introduces an efficient approach to protect the ownership by hiding iris code from iris recognition system into digital image for an authentication purpose using the integer wavelet transform based reversible watermarking scheme. An overview of integer wavelet transform is given in Section 3.2. A brief introduction to histogram modification is provided in Section 3.3. The proposed image authentication system is presented in Section 3.4. The experimental results and performance analysis are given in Section 3.5.

Chapter 4 exhibits an accurate authentication of an image using low density parity check and secure hash algorithm based iris recognition method with reversible watermarking
scheme based on integer wavelet transform and threshold embedding technique. The LDPC encoding and decoding schemes are presented in Section 4.2. Section 4.3 exhibits the lossless data hiding using IWT and threshold embedding technique. The idea of enrolment process of the proposed system is presented in Section 4.4. The verification process of the proposed system is discussed in Section 4.5. Some experimental results and performance analysis are given in Section 4.6.

An innovative biometric cryptosystem by adopting LDPC and SHA based iris recognition, biometric smart card security, and 512 bits AES scheme is presented in Chapter 5. An overview of the biometric smart card technology used in the thesis is given in Section 5.2. Section 5.3 exhibits the 512 bits AES scheme adopted for this scheme. The idea of encryption process of the proposed system is presented in Section 5.4. The decryption process of the proposed system is discussed in Section 5.5. The experimental results and performance analysis are given in Section 5.6.

A state-of-the-art method for continuous user authentication by integrating soft biometrics with non-orthogonal iris recognition is discussed in Chapter 6. Section 6.2 exhibits the color based facial and accessory soft biometric traits recognition. The idea of enrolment, verification and identification processes of non-orthogonal iris recognition system is presented in Section 6.3. The color based facial and accessory soft biometrics integrated with non-orthogonal iris recognition for continuous authentication is discussed in Section 6.4. Section 6.5 depicts the experimental results and performance analysis.

Finally, Chapter 7 summarizes the work presented in the thesis. This Chapter highlights the contributions of the research and the directions for future research.