Chapter 1 Introduction

“Knowledge itself is power” – (Francis Bacon)

Information Technology (IT) has become a vital part of the probably all fields of the world (i.e. Governance, industry, Defense, Health Science etc.). IT presents a tremendous impulsion to move forward in the 21st century with good quality and cost effective. Today more and more security-relevant data stored on computer systems and sharing of digital content is a common practice.

In this information age, Information security is the most important problem. Information security means protecting information and information systems from unauthorized access, use, disclosure, disruption, modification or destruction. Confidentiality, Integrity and Availability (known as the CIA triad) are the core principles of information security. Confidentiality is the term used to prevent the disclosure of information to unauthorized individuals or systems. Integrity means that data cannot be modified without authorization.

And for any information system to serve its purpose, the information must be Available when it is needed.

Digital Rights Management (DRM) system, also known as Intellectual Property Management and Protection (IPMP) systems in the MPEG-21 framework can satisfy the limiting access to only those people who have
acquired a proper license to play back the digital content. The aim of digital rights management system is to technically prevent the illegal copying digital content and abuse [1]. A key component of any digital rights management system is user authentication [2, 3]. There are many different verification technologies available, many of which have been in wide-spread commercial use for years. The most common person authentication or verification methods are

- **Something you know** - A Password, PIN (Personal Identification Number) or a piece of personal information (such as your favorite color);
- **Something you have** - A card Key, smart card, or token (like a Secure ID card) And
- **Something you are** - A Biometric [2]-[5].

Over time, the need for passwords, PIN, swipe cards, and tokens etc are slowly being replaced by uniquely identifying biometrics. Although public acceptance and the general understanding of the capabilities of this new technology obstruct the switch from tradition security systems, there are still immense rationales to use biometrics:

- **Increased security**: Tokens, swipe cards and keys can easily be theft by potential intruders, whereas acquiring a subject’s biometric requires specialist knowledge and equipment, and in most cases would not be possible without alerting the subject’s attention.
- **Reduced fraud**: It becomes extremely difficult for somebody to willingly give up his or her biometric data, so sharing identities (for “buddy punching” in time and attendance systems) is virtually impossible. In addition, because it becomes necessary to
expose one’s own biometric data (i.e. your own face), potential fraudsters are reluctant to attempt false verification.

- **Cost reduction:** By replacing plastic swipe cards, all cost associated with producing, distributing and replacing a lost card is completely eliminated.

1.1 Biometrics

Biometric are automated system which recognize a person/user by his/her physical or behavioral characteristics [5]. Physical characteristics are based on direct measurement of a part of the human body. For example Fingerprint, Iris-Scan, Retina-Scan, Hand Geometry, and Facial Recognition etc. Behavioral characteristics are based on action taken by the human. For example Voice Recognition, Keystroke-Scan, and Signature-Scan etc.

Figure 1-1 shows how a biometric system works; there are two functions in biometric system, Enrollment in which capture the chosen biometric, process the biometric, enroll the biometric template, and store the template. Verification in which live-scan the chosen biometric, process the biometric and extract the biometric template, match the scanned biometric template against stored template and answers “Is the person who they claim to be?”
1.2 Biometrics Technology Overview

A number of biometrics have been proposed, researched, and evaluated for identification (or verification) applications. Each biometrics has its strengths and limitations; and accordingly, each biometric appeal to a particular identification (authentication) application. A summary of the existing and burgeoning biometric technologies is described in this section.

1.2.1 DNA

DNA (Deoxyribo Nucleic Acid) is the one-dimensional ultimate unique code for one's individuality - with the exception that identical twins have the identical DNA pattern [4] [6] [7]. It is, however, currently used mostly in the context of forensic applications for identification. It has three limits

- DNA matching is not done in real-time
- Intrusive: a physical sample must be taken, while other biometric systems only use an image or a recording.
- Civil liberty issues and public perception

DNA evidence has been used in courts of law since 1985 to prove guilt or innocence. It is also used for paternity testing, identification of missing or dead people.

1.2.2 Ear

Human ear is a new class of relatively stable biometrics. The shape of the ear and the structure of the cartilaginous tissue of the pinna are distinctive. The features of an ear are not expected to be unique to each individual. The ear recognition approaches
are based on matching vectors of distances of salient points on the pinna from a landmark location on the ear and also appearance based [4] [8]-[11].

1.2.3 Face

The face of the person is considered to be the most immediate and transparent biometric for physical authentication. Many methods of face recognition have been proposed during last 40 years. The method of acquiring face images is non-intrusive [12]-[15].

Three primary approaches used for the verification based on face recognition: (i) Holistic matching methods: Use the whole face region as the raw input to a recognition system. One of the most widely used representations of the face region is eigenpictures, which are based on Principal Component Analysis (PCA). (ii) Feature-based matching methods: Local features such as the eyes, nose, and mouth are first extracted and their locations and local statistics are fed into a structure classifier. (iii) Hybrid methods: Uses both local features and the whole face region to recognize a face, a machine recognition system should use both [12].

1.2.4 Face Thermogram

Facial Thermogram employs the use of an infrared camera to capture the emission of heat patterns that are generated by the vascular system of the face [4] [16]. Heat that passes through facial tissue of a human being produces a unique and repeatable pattern. The captured pattern is converted into data and then compared to stored
patterns of authorized individuals, at which point possible matches are
generate along with probability percentages. The facial print does not
change over time and is accurate than facial geometry identification
technologies.

1.2.5 Fingerprint

Fingerprints are made of a series of ridges and
furrows on the surface of the finger (As shown
in Figure 1-6). Their formations depend on the
initial conditions of the embryonic development
and they are unique to each person (and each
finger). Typically, a fingerprint image is
captured with one of two ways: (i) scanning an
inked impression of a finger or (ii) using a live-scan fingerprint scanner
[4] [17]-[8].

Four basic approaches to identification based on fingerprint are
prevalent: (i) the invariant properties of the gray scale profiles of the
fingerprint image or a part thereof; (ii) global ridge patterns, also known
as fingerprint classes; (iii) the ridge patterns of the fingerprints; (iv)
fingerprint minutiae – the features resulting mainly from ridge endings
and bifurcations.

1.2.6 Gait

Gait is behavioral biometrics, it is
not supposed to be unique to each
individual, but is sufficiently
characteristic to allow identity
authentication [21]-[24]. Humans
are quite adept to recognize a
person at a distance from his gait.

Gait features are derived from an analysis of video-sequence footage.
1.2.7 Hand Geometry

Automated Hand Geometry system analyzes and measures the shape of the hand (As shown in Figure 1-8). That is it recognizes based on extraction of hand pattern like finger length, width, thickness, curvature, or relative location. Charge coupled device (CCD) cameras and infrared illumination used to take input; user puts his/her hand on highly reflective surface camera takes top and side view of the hand shape [4] [25]-[28].

1.2.8 Hand Vein

Nearly any part of vein in human body (such as retinal vein, facial vein, veins in hand) could be used for personal identification, but veins in hand are always preferred [4] [29] [30]. It is usually an uncovered part. Veins in hand (Figure 1-9) are closer to the surface than other organs, so the traits can be easier detected by low-resolution cameras.

1.2.9 Iris

Iris recognition is based on the visible qualities of the human iris. (As shown in Figure 1-10) visible characteristics include rings, furrows, freckles, and the iris corona. In most of the iris recognition systems use Iridian Technology in which visible characteristics converted into Iris-Code and this template use for verification [4] [31] [32].
1.2.10 Keystrokes

Keystroke dynamics is a behavioral biometric. The keystrokes of a person using a system could be monitored unobtrusively as that person is keying in other information. Keystroke dynamic features are based on time durations between the keystrokes. Some variants of identity authentication use features based on inter-key delays as well as dwell times - how long a person holds down a key. Typical matching approaches use neural network architecture to associate identity with the keystroke dynamics features [4] [33] [34].

1.2.11 Odor

The body odor biometrics is based on the fact that virtually each human smell is unique. The smell is captured by sensors that are capable to obtain the odor from non-intrusive parts of the body such as the back of the hand. Methods of capturing a person’s smell are being explored by Mastiff Electronic Systems (Figure 1-12). Each human smell is made up of chemicals known as volatiles. They are extracted by the system and converted into a template [4] [35].

1.2.12 Retinal Scan

Retina Scan System analyzes the layer of blood vessels situated at the back of the eye (As shown in Figure 1-13). The unique pattern of retina takes from a low intensity light source through an optical coupler. Retina scanning can be quite accurate but does require the user to look into a receptacle and focus on a given point [4] [36] [37].
1.2.13 Signature

Biometric signature recognition systems measures and analyze the physical activity of signing, such as the stroke order, the pressure applied and the speed. Some systems may also compare visual images of signatures, but the core of a signature biometric system is behavioral, i.e. how it is signed rather than visual, i.e. the image of the signature [4] [38] [39].

1.2.14 Voice Print

Voice is a behavioral biometrics. The speech signal conveys many levels of information to the listener (As shown in Figure 1-15). It conveys the message via words, but at other level speech conveys information about the language being spoken, the emotion, gender, and generally the identity of the speaker. The goal of the automatic voice recognition (Speaker Recognition) system is to extract characterize, and recognize the information in the speech conveying speaker identity. Speech is a behavioral signal that may not be consistently reproduced by a speaker, and can be affected by the emotions or the health of the speaker [4] [40]-[42].

1.3 Biometrics technologies comparative

Each biometric has the following desirable properties [4]:

- **Universality** Every person should have the characteristic.
- **Uniqueness** No two persons should be the same in terms of the characteristic.
- **Permanence** The characteristic should be invariant with time.
• **Collectability** The characteristic can be measured quantitatively.

• **Performance** The achievable identification accuracy.

• **Acceptability** Up to what extent people are willing to accept the biometric system.

• **Circumvention** How easy it is to fool the system by fraudulent techniques.

A comparison among common biometrics using the above seven properties is given in the Table 1-1. Analyzing the different available biometrics, it can be observed that no single biometric outstands according to all the criteria. Each biometric system has its own advantages and disadvantages.

<table>
<thead>
<tr>
<th>Biometrics</th>
<th>Universality</th>
<th>Uniqueness</th>
<th>Permanence</th>
<th>Collectability</th>
<th>Performance</th>
<th>Acceptability</th>
<th>Circumvention</th>
</tr>
</thead>
<tbody>
<tr>
<td>DNA</td>
<td>High</td>
<td>High</td>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>Low</td>
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<td>High</td>
<td>Medium</td>
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<td>Medium</td>
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<td>Low</td>
<td>Medium</td>
<td>High</td>
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<td>Low</td>
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<td>Face Thermogram</td>
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<td>Low</td>
<td>High</td>
<td>Medium</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
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<td>High</td>
<td>Medium</td>
<td>High</td>
<td>Medium</td>
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<td>High</td>
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<tr>
<td>Gait</td>
<td>Medium</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
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<td>Low</td>
<td>High</td>
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<tr>
<td>Hand Geometry</td>
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<td>Medium</td>
<td>Medium</td>
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<td>Medium</td>
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<tr>
<td>Hand Vein</td>
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<td>Medium</td>
<td>High</td>
<td>Medium</td>
<td>Medium</td>
<td>Medium</td>
<td>High</td>
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<tr>
<td>Iris</td>
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<td>High</td>
<td>High</td>
<td>Medium</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
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<tr>
<td>Keystrokes</td>
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<td>Low</td>
<td>Medium</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>Odor</td>
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<td>High</td>
<td>Low</td>
<td>Low</td>
<td>Medium</td>
<td>Low</td>
</tr>
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<td>Retinal Scan</td>
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<td>Medium</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Signature</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>Low</td>
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<tr>
<td>Voice Print</td>
<td>Medium</td>
<td>Low</td>
<td>Medium</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>Low</td>
</tr>
</tbody>
</table>

**Table 1-1 Comparison of Biometrics**

Figure 1-16 shows the current market share by biometric technology according to the *International Biometric Group (IBG)*. It can be observed that face recognition command on 11.4% of the market and was 19% in 2006.
1.4 Why Face Recognition?
Face recognition has been described as the Holy Grail of biometric systems, due to a number of significant advantages over other methods of biometric systems.

- **Non-intrusive:** Almost all other biometrics require some degree of user interaction in order to acquire biometric data, such as looking into an eye scanner or placing a finger on a fingerprint reader, accurate face recognition can be performed by simply glancing at a camera from a distance.

- **Public acceptance:** It has become apparent that face recognition systems generally receive a higher level of public acceptance than most other biometrics. This is perhaps partly due to the non-intrusive nature of face recognition as described above, but may also be the result of greater understanding and empathy of how the technology is capable of recognizing a face; it is well known that the public fear what they do not understand.

- **Existing databases:** One key hold-up for any large organization considering implementation of a biometric system is the amount
of time required in collection of a biometric database. Consider a police force using an iris recognition system. It would take a number of years before the database was of sufficient size to be useful in identifying suspects. Whereas large databases of high quality face images are already in place, so the benefits of installing a face recognition system are gained immediately after installation.

- **Analogy to human perception:** Perhaps the greatest advantage is that the biometric data required for face recognition (an image of a face) is recognizable by humans. This allows for an additional level of backup, should the system fail. A human reviewing the same biometric source (the reference image and live query image) can always manually check any identification or verification result.

However, with the current state of the art, these advantages do not include operating performance in terms of recognition accuracy. When compared with other biometric system, face recognition cannot compete with the low error rates achieved using iris or fingerprint recognition systems. However, no other biometric technology can match face recognition for its handiness of identification ‘at-a-glance’ or the advantages offered in being analogous to our own method of identification used by humans.

1.5 **Face Recognition**

Face recognition systems are built on computer program that analyze images of human faces for the purpose of identifying them [12]-[15].

Face recognition is accomplished in five steps

1. Image Acquisition: An image of the face acquired
2. Face Detection: Detect the locations of any faces in the acquired images
3. Feature Extraction: Analyze the spatial geometry of distinguishing features of the face.

4. Face Matching
   a. Verification: The general template is only compared with one template in the database that of the claimed identity.
   b. Identification: This process yields scored that indicates how closely the generated template matches each of those in the database.

5. Result: On the basis of score obtained from fourth step declare a match.

1.5.1 History
Automated face recognition is a relatively new concept that was developed in the 1960s; the first semi-automated system for face recognition required the administrator to locate features (eyes, ears, nose, and mouth) on the photographs before it calculated distances and ratios to a common reference point, which were then compared to reference data. In the early 1970s, Goldstein, Harmon, and Lesk used 21 specific subjective markers such as hair color and lip thickness to automate the recognition [43]-[45]. This proved even harder to automate due to the subjective nature of many of the measurements still made completely by hand. The problem with both of these early solutions was that the measurements and locations were manually computed. In 1987-88, Kirby and Sirovich applied principle component analysis, a standard linear algebra technique, to the face recognition problem [46] [47]. This was considered somewhat of a milestone as it showed that less than one hundred values were required to accurately code a suitably aligned and normalized face image. In 1991, Turk and Pentland discovered that while using the eigenfaces techniques, the residual error could be used to detect faces in images – a discovery that enabled reliable real-time
automated face recognition systems [48]. Although the approach was somewhat constrained by environmental factors, it nonetheless created significant interest in furthering development of automated face recognition technologies. The technology first captured the public’s attention from the media reaction to a trial implementation at the January 2001 Super Bowl, which captured surveillance images and compared them to a database of digital mug shots. This demonstration initiated much-needed analysis on how to use the technology to support national needs while being considerate of the public’s social and privacy concerns. Today, face recognition technology is being used to combat passport fraud, support law enforcement, identify missing children, and minimize benefit/identity fraud [12]-[14].

1.5.2 Face Recognition from Still Images
There are the following categorizations of face recognition approaches:

1. **Holistic matching methods:** These methods use the whole face region as the raw input to a recognition system. One of the most widely used representations of the face region is eigenpictures [46]-[48], which are based on principal component analysis.

2. **Feature-based (structural) matching methods:** Typically, in these methods, local features (eyes, nose, and mouth) are first extracted and their locations and local statistics (geometric and/or appearance) are fed into a structural classifier.

3. **Hybrid methods:** Just as the human perception system uses both local features and the whole face region to recognize a face, a machine recognition system should use both. One can argue that these methods could potentially offer the better of the two types of methods.

Within each of these categories, further classification is likely as In Table 1-2,
1.5.2.1 Holistic Approaches

- **Principal-Component Analysis**
  
  After the success of low dimensional reconstruction of faces using Karhunen-Loeve (KL) or PCA projections [Kirby and Sirovich 1987, 1990], eigenpictures has been one of the major driving forces behind face representation, detection, and recognition. It is illustrious that there exist considerable statistical redundancies in natural images [49]. For a limited class of objects such as face images that are normalized with respect to transformations (i.e. scale, translation, and rotation), the redundancy is even greater [50] [51]. One of the best global compact representations is KL/PCA, which decorrelates the outputs.

<table>
<thead>
<tr>
<th>Approach</th>
<th>Representative Work</th>
</tr>
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<tbody>
<tr>
<td><strong>Holistic methods</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Principal Component Analysis (PCA)</strong></td>
<td>Direct Application of PCA</td>
</tr>
<tr>
<td>Eigenfaces</td>
<td>Two-class problem with prob. Measure</td>
</tr>
<tr>
<td>Probabilistic Eigenfaces</td>
<td>FLD on eigenspace</td>
</tr>
<tr>
<td>Fishfaces/Subspaces LDA</td>
<td>Two-class problem based on SVM</td>
</tr>
<tr>
<td>SVM</td>
<td>Enhanced GA learning</td>
</tr>
<tr>
<td>Evolution Pursuit</td>
<td>Point-to-line distance based</td>
</tr>
<tr>
<td>Feature Lines</td>
<td>ICA-based feature analysis</td>
</tr>
<tr>
<td>ICA</td>
<td></td>
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<tr>
<td><strong>Other Representations</strong></td>
<td></td>
</tr>
<tr>
<td>LDA/FLD</td>
<td>FLD/LDA on raw image</td>
</tr>
<tr>
<td>PDBNN</td>
<td>Probabilistic decision based NN</td>
</tr>
<tr>
<td><strong>Feature-based methods</strong></td>
<td></td>
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<tr>
<td>Pure geometry methods</td>
<td>Earlier methods; recent methods</td>
</tr>
<tr>
<td>Dynamic Link Architecture</td>
<td>Graph matching methods</td>
</tr>
<tr>
<td>Hidden Markov Model</td>
<td>HMM methods</td>
</tr>
<tr>
<td>Convolution Neural Network</td>
<td>SOM learning based CNN methods</td>
</tr>
<tr>
<td><strong>Hybrid methods</strong></td>
<td></td>
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<tr>
<td>Modular Eigenfaces</td>
<td>Eigenfaces and eigen modules</td>
</tr>
<tr>
<td>Hybrid LFA</td>
<td>Local feature method</td>
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<td>Shape-normalized</td>
<td>Flexible Appearance models</td>
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<tr>
<td>Component-based</td>
<td>Face region and components</td>
</tr>
</tbody>
</table>

Table 1-2 Still Face Recognition Techniques

An advantage of using such representations is their reduced sensitivity to noise. Some of this noise may be due to small occlusions, as long as the topological structure does not change.
Eigenface
The first successful demonstration of machine recognition of human faces was made by Turk and Penland in 1991 using eigenpictures (also known as eigenfaces) for face detection and identification [48]. Given the eigenfaces, every face in the database can be represented as a vector of weights; the weights are obtained by projecting the image into eigenface components by a simple inner product operation. When a new test image whose identification is required is given, its vector of weights also represents the new image. Locating the image in the database does the identification of the test image whose weights are the closest to the weights of the test image. By using the observation that the projection of a face image and a non-face image are usually different, a method of detecting the presence of a face in a given image is obtained. The method was demonstrated using a database of 2500 face images of 16 subjects, in all combinations of three head orientations, three head sizes, and three lighting conditions.

Probabilistic Eigenfaces
Using a probabilistic measure of similarity, instead of the simple Euclidean distance used with eigenfaces, the standard eigenfaces approach was extended [52] to a Bayesian approach. Practically, the estimation of probability distributions in a high dimensional space from very limited numbers of training samples per class is a major drawback of a Bayesian method. To avoid this, a much simpler two-class problem was created from the multiclass problem by using a similarity measure based on a Bayesian analysis of image differences. A large performance improvement of this probabilistic matching technique over standard nearest-neighbor eigenspace matching was reported using large face datasets including the FERET database [53].
Fisherfaces/Subspaces LDA

Face recognition systems using LDA/FLD have also been very successful. LDA training is carried out via scatter matrix analysis [54]. Discriminant analysis of eigenfeatures is applied in an image retrieval system to determine not only class (human face vs. non-face) but also individuals within the face class [55]. Using tree-structure learning, the eigenspace and LDA projections are recursively applied to smaller and smaller sets of samples. Such recursive partitioning is carried out for every node until the samples assigned to the node belong to a single class. A set of 800 images was used for training; the training set came from 42 classes, of which human faces belong to a single class. Within the single face class, 356 individuals were included and distinguished. Testing results on images not in the training set were 91% for 78 face images and 87% for 38 non-face images based on the top choice [56]. To improve the performance of LDA based systems, in 1998-99 a regularized subspace LDA system that unifies PCA and LDA was proposed by Zhao [51] [57]. Good generalization ability of this system was demonstrated by experiments that carried out testing on new classes/individuals without retraining the PCA bases $\Phi$, and sometimes the LDA bases $W$. While the reason for not retraining PCA is obvious, it is interesting to test the adaptive capability of the system by fixing the LDA bases when images from new classes are added. At least one of the following three characteristics separates this system from other LDA based systems: (1) the unique selection of the universal face subspace dimension, (2) the use of a weighted distance measure, and (3) a regularized procedure that modifies the within-class scatter matrix $S_w$. The authors selected the dimensionality of the universal face subspace based on the characteristics of the eigenvectors (face-like or not) instead of the eigenvalues as is commonly done. Later it was concluded that the global face subspace dimensionality is on the order of 400 for large
A weighted distance metric in the projection space $z$ was used to improve performance [51]. Finally, the LDA training was regularized by modifying the $S_w$ matrix to $S_w + \delta I$, where $\delta$ is a relatively small positive number. Doing this solves a numerical problem when $S_w$ is close to being singular. In the extreme case where only one sample per class is available, this regularization transforms the LDA problem into a standard PCA problem with $S_b$ being the covariance matrix $C$. Applying this approach, without retraining the LDA basis, to a testing/probe set of 46 individuals of which 24 were trained and 22 were not trained (a total of 115 images including 19 untrained images of no frontal views), the authors reported the following performance based on a front-view-only gallery database of 738 images: 85.2% for all images and 95.1% for frontal views.

**EP – Evolution Pursuit**
An Evolution Pursuit (EP) based adaptive representation and its application to face recognition was presented by Liu and Wechsler in 2000. In analogy to projection pursuit methods, EP seeks to learn an optimal basis for the dual purpose of data compression and pattern classification. In order to increase the generalization ability of EP, a balance is sought between minimizing the empirical risk encountered during training and narrowing the confidence interval for reducing the guaranteed risk during future testing on unseen data [59]. Toward that end, EP implements strategies characteristic of genetic algorithms (GAs) for searching the space of possible solutions to determine the optimal basis. EP starts by projecting the original data into a lower-dimensional whitened PCA space. Directed random rotations of the basis vectors in this space are then searched by GAs where evolution is driven by a fitness function defined in terms of performance accuracy (empirical risk) and class separation (confidence interval). The feasibility of this
method has been demonstrated for face recognition, where the large number of possible bases requires a greedy search algorithm. The particular face recognition task involves 1107 FERET frontal face images of 369 subjects; there were three frontal images for each subject, two for training and the remaining one for testing. The authors reported improved face recognition performance as compared to eigenfaces by Turk and Pentland [48], and better generalization capability than Fisherfaces [60].

- **ICA – Independent Component Analysis**
  Independent-component analysis is a generalization of principal-component analysis, which decorrelates the high-order moments of the input in addition to the second-order moments and used to extract the features of face recognition [61].

  Using ICA two architectures have been proposed for face recognition, the first is used to find a set of statistically independent source images that can be viewed as independent image features for a given set of training images and the second is used to find image filters that produce statistically independent outputs (a factorial code method) [62] [63]. In both architectures, PCA is used first to reduce the dimensionality of the original image size (60 × 50). ICA is performed on the first 200 eigenvectors in the first architecture, and is carried out on the first 200 PCA projection coefficients in the second architecture. The authors reported performance improvement of both architectures over eigenfaces in the following scenario: a FERET subset consisting of 425 individuals was used; all the frontal views (one per class) were used for training and the remaining (up to three) frontal views for testing.

- **Other Representations**
  In addition to the popular PCA representation and its derivatives such as ICA and EP, other features have also been used, such as raw intensities
and edges. A fully automatic face detection/recognition system based on a neural network is reported in 1997 [64]. The proposed system is based on a probabilistic decision-based neural network (PDBNN, an extended (DBNN) [65]) that consists of three modules: a face detector, an eye localizer, and a face recognizer. Unlike most methods, the facial regions contain the eyebrows, eyes, and nose, but not the mouth. The rationale of using only the upper face is to build a robust system that excludes the influence of facial variations due to expressions that cause motion around the mouth. To improve robustness, the segmented facial region images are first processed to produce two features at a reduced resolution of 14×10: normalized intensity features and edge features, both in the range [0, 1]. These features are fed into two PDBNNs and the final recognition result is the fusion of the outputs of these two PDBNNs. A unique characteristic of PDBNNs and DBNNs is their modular structure. Compared to most multiclass recognition systems that use discrimination function between any two classes, PDBNN has a lower false acceptance/rejection rate because it uses the full density description for each class. In addition, this architecture is beneficial for hardware implementation such as distributed computing. However, it is not clear how to accurately estimate the full density functions for the classes when there are only limited numbers of samples. Further, the system could have problems when the number of classes grows exponentially.

1.5.2.2 Feature Based Approaches
Many methods in the structural matching category have been proposed; including many early methods based on geometry of local features [66] [67] as well as 1D [68] and pseudo-2D [69] HMM methods. One of the most successful of these systems is the Elastic Bunch Graph Matching (EBGM) system [70] [71], which is based on DLA [72] [73]. Wavelets,
especially Gabor wavelets, play a building block role for facial representation in these graph-matching methods. A typical local feature representation consists of wavelet coefficients for different scales and rotations based on fixed wavelet bases. These locally estimated wavelet coefficients are robust to illumination change, translation, distortion, rotation, and scaling.

- **DLA**
  DLAs attempt to solve some of the conceptual problems of conventional artificial neural networks, the most prominent of these being the representation of syntactical relationships in neural networks. DLAs use synaptic plasticity and are able to form sets of neurons grouped into structured graphs while maintaining the advantages of neural systems. Both Buhmann et al. [72] and Lades et al. [73] used Gabor-based wavelets as the features. DLA’s basic mechanism, in addition to the connection parameter $T_{ij}$ between two neurons $(i, j)$, is a dynamic variable $J_{ij}$ [73]. Only the $J$-variables play the roles of synaptic weights for signal transmission. The $T$-parameters merely act to constrain the $J$-variables; Recognition of a new image takes place by transforming the image into the grid of jets, and matching all stored model graphs to the image. Conformation of the DLA is done by establishing and dynamically modifying links between vertices in the model domain.

- **EBGM**
  The DLA architecture was extended to Elastic Bunch Graph Matching [71]. This is similar to the graph described above, but instead of attaching only a single jet to each node, the authors attached a set of jets (called the bunch graph representation), each derived from a different face image. To handle the pose variation problem, the pose of the face is first determined using prior class information [74], and the “jet”
transformations under pose variation are learned [75]. The success of the EBGM system may be due to its resemblance to the human visual system [76].

1.5.2.3 Hybrid Approaches

- **Modular Eigenfaces**
  Hybrid approaches use both holistic and local features. For example, the modular eigenfaces approach uses both global eigenfaces and local eigenfeatures [77]. In mug shot applications, usually a frontal and a side view of a person are available; in some other applications, more than two views may be appropriate. One can take two approaches to handling images from multiple views. The first approach pools all the images and constructs a set of eigenfaces that represent all the images from all the views. The other approach uses separate eigenspaces for different views, so that the collection of images taken from each view has its own eigenspace. The second approach, known as *view-based eigenspaces*, performs better.

  The concept of eigenfaces can be extended to eigenfeatures, such as eigeneyes, eigenmouth, etc. Using a limited set of images (45 persons, two views per person, with different facial expressions such as neutral vs. smiling), recognition performance as a function of the number of eigenvectors was measured for eigenfaces only and for the combined representation. For lower-order spaces, the eigenfeatures performed better than the eigenfaces [77]; when the combined set was used, only marginal improvement was obtained. These experiments support the claim that feature-based mechanisms may be useful when gross variations are present in the input images.

- **Hybrid LFA**
  It has been argued that practical systems should use a hybrid of PCA and LFA [50]. Such view has been long held in the psychology community [78]. It seems to be better to estimate eigenmodes/eigenfaces that have
large eigenvalues (and so are more robust against noise), while for estimating higher-order eigenmodes it is better to use LFA. LFA is an interesting biologically inspired feature analysis method [50].

- **Shape-normalized (Flexible Appearance models)**
  A flexible appearance model based method for automatic face recognition was presented in [79]. To identify a face, both shape and gray-level information are modeled and used. The shape model is an ASM; these are statistical models of the shapes of objects, which iteratively deform to fit to an example of the shape in a new image. The statistical shape model is trained on example images using PCA, where the variables are the coordinates of the shape model points. For the purpose of classification, the shape variations due to interclass variation are separated from those due to within-class variations (such as small variations in 3D orientation and facial expression) using discriminant analysis. Based on the average shape of the shape model, a global shape-free gray level model can be constructed, again using PCA. To further enhance the robustness of the system against changes in local appearance such as occlusions, local gray-level models are also built on the shape model points. Simple local profiles perpendicular to the shape boundary are used. Finally, for an input image, all three types of information, including extracted shape parameters, shape-free image parameters, and local profiles, are used to compute a Mahalanobis distance for classification. Based on training 10 and testing 13 images for each of 30 individuals, the classification rate was 92% for the 10 normal testing images and 48% for the three difficult images.

- **Component-based**
  The basic idea of component-based methods is to decompose a face into a set of facial components such as mouth and eyes that are interconnected by a flexible geometrical model [80]. Notice how this
method is similar to the EBGM system except that gray-scale components are used instead of Gabor wavelets.) The motivation for using components is that changes in head pose mainly lead to changes in the positions of facial components, which could be accounted for by the flexibility of the geometric model. However, a major drawback of the system is that it needs a large number of training images taken from different viewpoints and under different lighting conditions. To overcome this problem, the 3D morphable face model is applied to generate arbitrary synthetic images under varying pose and illumination [81]. Only three face images (frontal, semiprofile, profile) of a person are needed to compute the 3D face model. Once the 3D model is constructed, synthetic images of size 58 x 58 are generated for training both the detector and the classifier. Specifically, the faces were rotated in depth from 0° to 34° in 2° increments and rendered with two illumination models (the first model consists of ambient light alone and the second includes ambient light and a rotating point light source) at each pose. Fourteen facial components were used for face detection, but only nine components that were not strongly overlapped and contained gray-scale structures were used for classification. In addition, the face region was added to the nine components to form a single feature vector (a hybrid method), which was later trained by a SVM classifier [59]. Training on three images and testing on 200 images per subject led to the following recognition rates on a set of six subjects: 90% for the hybrid method and roughly 10% for the global method that used the face region only; the false positive rate was 10%.

1.6 Thesis Rationale and Objective
Face recognition has been a very challenging and difficult problem. Inspite of the great work done in the last four decades, it can be sure that the face recognition research community will have work to do during, at
least, the next two decades to completely solve the problem. Strong and coordinated effort between the computer visions, signal processing, psychophysics and neurosciences communities are needed [82]. Facial recognition revenues are projected to grow from $34.4m in 2002 to $429.1m in 2007 and are expected to comprise approximately 10% of the entire biometric market [83]. Percentage of face recognition in Biometric Market increases through 12.4% in 2002 to 19% in 2006[84].

Identified objectives of the work are

- Identify the problems associated with existing face recognition systems and possible avenues of research.
- Development of the most effective method from the range of PCA based face recognition techniques, in order to achieve a more effective face recognition technique.
- Performance evaluation of developed methodology with the existing one.

1.7 Research Contributions

The research contributions of this thesis are as follows

- Literature review on PCA based face recognition techniques
- New experimental studies of PCA and KPCA based face recognition system
- Proposed a Novel Superior PCA based face recognition
- Effect of Feature Normalization on PCA based face recognition system
  - Unit Length,
  - Zero Mean & Unit Variance
  - Linear Scaling to Unit Range and
  - Rank Normalization
- Effect of Similarity Measures on PCA based face recognition system.
1.8 Organization of Thesis
Chapter 1 gives the introduction to information security, digital rights management, biometrics, and brief introduction to still image based face recognition system. It also covers the thesis rationale, objective of research and contribution of work. Chapter 2 covers the brief review of the PCA based face recognition techniques, proposed methodologies has been introduced in Chapter 3. Chapter 4 gives the Experiments, results and discussion and Conclusion and future work has been given in Chapter 5.
References


35. Z. Korotkaya, “Biometric Person Authentication: Odor”


82. L. Torres, “Is there any hope for face recognition?”, Proc. of the 5th International Workshop on Image Analysis for Multimedia Interactive Services, Lisboa, Portugal, 21-23 April 2004


84. http://www.biometricgroup.com