AUTOMATED BIOMETRICS OF AUDIO-VISUAL MULTIPLE MODALS

By

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ABSTRACT

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Biometrics is the science and technology of measuring and analyzing biological data for authentication purposes. Its progress has brought in a large number of civilian and government applications. The candidate modalities used in biometrics include retinas, fingerprints, signatures, audio, faces, etc.

There are two types of biometric system: single modal systems and multiple modal systems. Single modal systems perform person recognition based on a single biometric modality and are affected by problems like noisy sensor data, intra-class variations, distinctiveness and non-universality. Applying multiple modal systems that consolidate evidence from multiple biometric modalities can alleviate those problems of single modal ones.

Integration of evidence obtained from multiple cues, also known as fusion, is a critical part in multiple modal systems, and it may be consolidated at several levels like feature fusion level, matching score fusion level and decision fusion level.

Among biometric modalities, both audio and face modalities are easy to use and generally acceptable by users. Furthermore, the increasing availability and the low cost of audio and visual instruments make it feasible to apply such Audio-Visual (AV) systems for security applications. Therefore, this dissertation proposes an algorithm of face recognition. In addition, it has developed some novel algorithms of fusion in different levels for multiple modal biometrics, which have been tested by a virtual database and proved to be more reliable and robust than systems that rely on a single modality.

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1 INTRODUCTION

The traditional five senses, including sighting, hearing, touching, smelling and tasting, help a person to capture a rich amount of information to his or her brain. The brain then analyzes, classifies, recognizes and interprets the information very quickly and accurately. It is a kind of miracle that human brains have such amazing capabilities to intuitively use intrinsic physiological or behavioral traits to process newly acquired information for the purpose of human recognition in an efficient manner. Such physiological or behavioral traits can come from face, gait, signature, hand geometry, fingerprint, ear print or voice.

Today, surveillance videos have been installed almost everywhere for safety consideration, digital libraries are convenient for people to use, and forensic work and law enforcement need to identify an individual very fast and accurately. The above wide varieties of applications require reliable and robust authorization methodologies to automatically verify the identity of an individual. Among available authorization methods, biometrics can automatically identify an individual based on his or her physiological or behavioral traits by computers. Such technology has received a great amount of attention for safety and security in nearly all aspects of our daily lives. Especially, after 9.11 terrorist attacks in New York City, public interest in biometrics is picked up all over the world very quickly, and many governments are heavily funding biometric research.

Passwords and ID cards have been used for a quiet while for people to obtain the permission of accessing security systems, but those methods can easily be breached and are unreliable to some degrees. But, it will be another story if people consider their biometric traits as their own passwords, because that will be extremely difficult for someone else to simulate or copy other people's biometric traits or cues to access restricted security systems, because those traits or cues from biometrics are unique for everyone [33], and they cannot be borrowed, stolen, or forgotten.

There are many biometric modalities based on characteristics that are unique for everyone. These characteristics include fingerprints, hand geometry, iris, retina, signature, face and voice. It has been demonstrated that these characteristics can be used to positively identify a person.

This dissertation emphasizes on automatic person recognition by using multiple modal biometrics. An experiment virtual database is constructed with text-independent audio signals and still faces images. And it is used to test the proposed algorithms in this dissertation. Meanwhile, a framework for the multiple modal systems is proposed, under which biometric fusion for person recognition can be done in feature level. Also, this dissertation explores a new face recognition method to extract facial features and recognize person by only face modality. Then it develops several novel algorithms to combine visual and audio information at feature and matching score level for multiple modal recognition.

In this chapter, the basics of biometrics are introduced, research motivation and contributions are presented, and towards the end, the dissertation is outlined.

1.1 Basics of Biometric Systems

Automatic biometrics, which often employs pattern recognition techniques, uses individual's physiological or behavioral characteristics to recognize a person automatically. In our daily life, biometrics can be utilized alone or integrated with other technologies such as smart cards, encryption keys and digital signatures. The technologies based on biometrics are becoming the foundation of highly secure identification and personal verification solutions.

There are two modes for a biometric system to recognize a subject: verification or identification (Fig. 1.1 and Fig. 1.2) [33]. Between both of them, identification will compare the acquired biometric information with the templates corresponding to all users in the database. On the other hand, verification only concerns about the comparison result with those templates corresponding to the claimed identity.

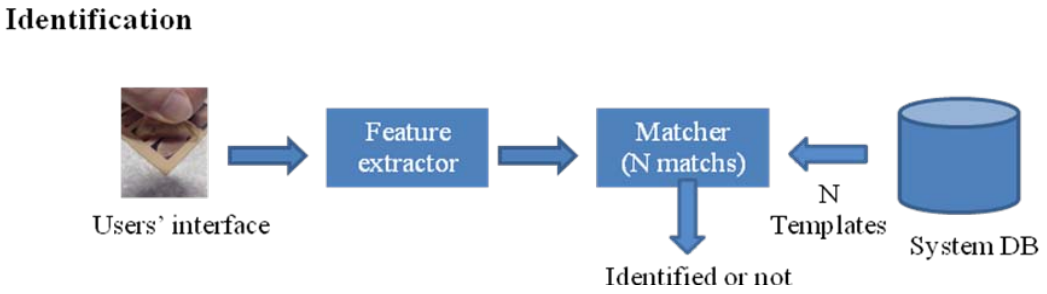


Figure 1.1 An identification procedures

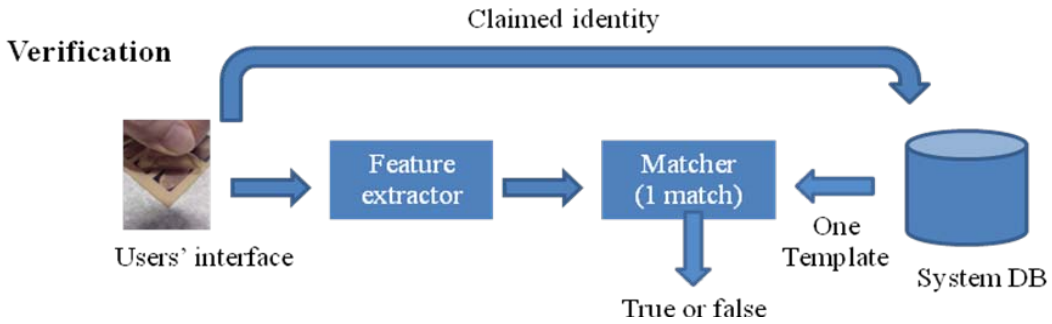


Figure 1.2 A verification procedures

Biometric authentication can be found almost everywhere, penetrating our daily life. Many applications are already benefiting from these technologies, for example, government IDs, criminal investigation, finding missing persons, secure e-banking, investment transactions, healthcare and other social services.

Practically, all biometric authentication systems work in the same manner. First, a person is enrolled into a database using a specified method. Biometric data about certain characteristics of the person is captured. The data is usually fed through an algorithm that turns the data into a code stored in a database. When the person needs to be identified, the system will acquire new data about the person again, extract new code from this newly acquired data with the algorithm, and then compare the new code with the ones in the database to see if there is a match.

In general, there are some advantages and disadvantages in the recognition techniques based on biometrics, as summarized in Table 1.1.

Advantages	Disadvantages
Accurate recognition	Unacceptable by public: some biometrics
Unique biometric traits	Legal problems: some biometrics
Fast, automatic recognition	Big data storage amount
Safe	Privacy problem

Table 1.1 General advantages/disadvantages of biometrics

The advantages normally outweigh the disadvantages because:

1) As an identification tool, it has the potential of recognizing subjects accurately;
2) Biometric traits are unique to everyone [33] and the person himself is a key to access the security system;
3) One can't lose, forget, or share his biometric information and it is known positively that the valuable information cannot be falsified.

There are many modalities that can be utilized as biometric traits and cues. Depending on the number of modalities used, biometric systems can be either single modal or multiple modal systems [33].

Single modal biometric systems perform person recognition based on a single source of biometric data and are likely affected more by the problems like noisy sensor data, intra-class variations, distinctiveness and non-universality [53].

Multiple modal biometric systems capture two or more biometric data. Fusion techniques are applied to combine and analyze the data in order to produce (hopefully) a better recognition rate. Such technologies can not only overcome the restriction and shortcomings from single modal systems, but also probably produce lower error rates in recognizing persons.

Biometric fusion is the process of combining information from multiple biometric readings, either before, during or after a decision has been made regarding identification or authentication from a single biometric [51]. The data information from those multiple modals can be combined in several levels: sensor, feature, score and decision level fusions [18, 19].

1.2 Motivation

1.2.1 Why multiple modal biometrics?

In biometrics systems, although single modal based person recognition has been shown to be effective in a controlled environment, its performance easily degrades in the presence of a mismatch between training and testing conditions. For example, for a face based system, although it is probably one of the most user-friendly biometric recognition methods available so far, it can be sensitive to illumination and pose variation, which will limit its range of applications greatly. For a speech based system, channel distortion, coder distortion and/or ambient noise pose challenges to recognize a person [37].

To cope with some limitations of single modal biometric systems, multiple modal biometric systems, which use more than one biometric at a time, have been introduced for person recognition. A multiple modal system is often comprised of several modality experts and a decision module. Since it uses complimentary discriminative information, lower error rates may be achieved. And such a system may also be more robust due to the fact that the degradation in performance of one modality affected by environmental conditions may be compensated by another modality.

1.2.2 Biometric fusion algorithms in several levels

Although people can obtain numerous biometric data from different modalities, those data have to be combined in a way to facilitate person recognition. Biometric fusion, which integrates information from modality experts, is a critical part of any multi-modal recognition biometric system. It can happen at different levels: feature, score, and decision levels.

In this dissertation, a person recognition system implemented combines biometric data at different fusion levels within a common framework. Integrating feature data extracted from different modalities is a higher level fusion, which can keep more information than other level fusions such as score and decision levels. Meanwhile, in the relevant literature about audio-visual (AV) person recognition, results from the feature level fusion have yet to be seen.

1.2.3 AV systems

As mentioned above, the candidate modality experts used in multiple modal biometrics can be retinas, irises, fingerprints, hand geometries, handwriting signatures, audio and faces. It is important to note that some techniques, such as retinal scanning or finger print recognition, may have better accuracy, but may not be appropriate for certain people or applications [33]. Moreover, some of these techniques need a high level of co-operation by potential users, but some users feel uncomfortable to cooperate.

Both audio and face (visual) recognition are considered to be easy to use and normally acceptable by many people. They need minimal co-operation from people, and are not deemed to attack the privacy of the individuals to certain degree, because this is the normal way in which humans recognize their fellows. Another advantage of audio and face recognition is that people do it every day, without much effort. This makes them ideal for the applications, which require continuous monitoring. The increasing availability and the low cost of audio and visual sensors make it feasible to deploy such systems for access control and monitoring. These motivate us to pursue research in the direction of audio-visual (AV) based person recognition.

In an AV system, one biometric modality expert is the audio signal. Audio-based authentication systems can be classified into two categories: *text-dependent* and *text-independent* [3]. Methods from these two categories use different speaker models for their implementation. In a text-dependent system, speakers must recite a phrase, password or numbers specified by the system. An often-used approach in this case is Hidden Markov Model (HMM). This is in contrast to a text-independent system, where speakers can say whatever they want to say. In the latter case, one of popular speaker models is Gaussian Mixture Models **(**GMM) [3]. A principal advantage of a text-independent technique is the general absence of idiosyncrasies in the task definition, which allows the technique to be applied to many applications. For this reason, this dissertation employs text-independent speech as case studies.

Recent AV person recognition techniques use video to improve recognition rate, though this will aggravate the problem of storage and computation in a large biometric authentication system. Methods published in the literature include using lip movement or partial face images to represent visual cue in AV systems [53, 58]. In this research, we use still face images to reduce storage space and computational complexity.

1.2.4 Differences between this research and others

The major differences between this research and those given in the literature are summarized as follows:

1) This research is concerned about different level fusions of multiple modal biometric data under a unified framework.
2) This dissertation emphasizes on the integration of audio and visual (AV) feature vectors by different methods.

3) The methodologies about the feature level fusion of AV can easily be extended to other multiple modal systems.

4) The proposed/modified algorithms for feature level fusion have been tested and proved by integrating text-independent speech signals with still images of whole faces. As to AV-based feature level fusion, other published methods may have used text-independent speech signals, video signals, lip movement, or partial face images.

Furthermore, this research studies the feasibility of using a common framework to investigate fusion of audio and visual information at score and decision levels. Also, the proposed algorithms of biometric fusion in these levels have been tested.

1.2.5 Summary of Motivations

As mentioned above, the candidate modality experts used in multiple modal biometrics can be retinas, irises, fingerprints, hand geometries, handwriting signatures, audio and faces. It is important to note that some techniques, such as retinal scanning or finger print recognition, may offer better accuracy, but may not be appropriate for certain applications [33]. Moreover, some of these techniques need a high level of co-operation by potential users or possess social or psychological factors that may prove unacceptable to certain users. On the other hand, both audio and face (visual) recognition are considered to be easy to use and normally acceptable by users. They need minimal co-operation from users and are not deemed to erode the privacy of the individuals to certain degree, because this is the normal way in which humans recognize their fellows. Another advantage of audio and face recognition is that people do it every day, without much effort. This makes them ideal for online applications or applications where continuous

monitoring may be required. The increasing availability and the low cost of audio and visual sensors make it feasible to deploy such systems for access control and monitoring. These motivate us to pursue research in the direction of audio-visual (AV) based person recognition.

In an AV system, one biometric modality expert is the audio signal. Audio-based authentication systems can be classified into two categories: *text-dependent* and *text-independent* [3]. Methods from these two categories use different speaker models for their implementation. In a text-dependent system, speakers must recite a phrase, password or numbers specified by the system. An often-used approach in this case is Hidden Markov Model (HMM). This is in contrast to a text-independent system, where speakers can say whatever they wish to say. In the latter case, one of popular speaker models is Gaussian Mixture Models **(**GMM) [3]. A principal advantage of a text-independent technique is the general absence of idiosyncrasies in the task definition, which allows the technique to be applied to many applications. For this reason, this dissertation concentrates on the problem of text-independent speaker recognition.

Recent AV person recognition techniques use video to improve recognition rate, though this will aggravate the problem of storage and computation in a large biometric authentication system. Methods published in the literature include using lip movement or partial face images to represent visual cue in AV systems. In this research, we use still face images to reduce storage space and computational complexity.

1.3 Contributions

The contributions of this research are summarized below:

1) Proposed a face recognition algorithm, applied Pyramidal Gabor Wavelet and Eigenface (PGE) algorithms and studied their efficiency.
2) Proposed a common framework for feature level and used in the proposed AV person recognition system.
3) Proposed a novel algorithm of feature stream to fuse features from different modalities by synchronizing and sequencing the biometric traits; and investigated its performance against the single modal techniques involved.
4) Developed and modified a number of optimization algorithms at feature level fusion by applying Genetic algorithm, simulated annealing, etc.
5) Introduced a score fusion method and applied Golden Ratio method (GR) to integrate information from both modalities at matching score level;
6) Constructed a virtual database to test the above algorithms.

Several papers about this research have been published or submitted for publication. Meanwhile, more papers are under preparation.

1.4 Outline of the Dissertation

The dissertation is organized as follows.

- Chapter 1 introduces the basics of biometrics, motivations and contributions of the research, and gives outline of the dissertation.
- Chapter 2 surveys briefly the existing single modal and multiple modal biometric systems.
- Chapter 3 discusses a face recognition method based on the Pyramidal Gabor wavelet and Eigenface (PGE) conception, and then presents the PGE algorithm, along with results from experiment studies.

- Chapter 4 studies the text-independent speaker recognition method. It briefly reviews Mel Frequency Cepstral Coefficients (MFCC) algorithm, a procedures for speaker recognition together with the GMM and Expectation Maximization (EM) algorithms. It also presents experimental results using the speaker recognition procedure with a database constructed for this research.
- Chapter 5 gives an introduction about information fusion, proposes a framework to unify fusion strategies in the feature fusion level, devises an algorithm to perform feature fusion, and reports the relevant test results using an AV database constructed for this research.
- Chapter 6~9 propose an algorithm of feature stream for feature fusion, introduce and modify couples of optimization algorithms of feature fusion, and report the test results with the same database.
- Chapter 10 discusses score level fusion, and then introduces Golden Ratio (GR) algorithm for score fusion. Finally, test results for the algorithm are given.
- Chapter 11 summarizes the contribution of this research and outlines possible future research endeavors.

2 SURVEY OF BIOMETRICS

2.1 Introductory

As security breaches and swindle behavior increase, it becomes very urgent and necessary to develop highly secure identification and verification technologies. As mentioned in the previous chapter, biometrics can provide better solutions for confidential and personal privacy security. Such a technology is based on individual characteristics of his (her) physiologies or behaviors. Among those human characteristics, we know that not all of them can be served as biometric traits or cues. Only those satisfying the following factors may be applied to recognize a subject under the test [33]:

1) It requires that every individual has distinctive/unique traits.
2) There are not too many restrains or limitations to collect biometric samples from potential users.
3) Each individual has such physiology or behavior.
4) Accurate and fast recognition results must be provided.
5) It is acceptable to users.
6) It can avoid or prevent various fraudulent uses or invasion.

Due to its higher level of security, biometrics has been penetrated almost all arenas of economy and people's daily lives. Meanwhile, it can be utilized alone or integrated with other technologies in order to offer a more reliable and robust strategy to determine or confirm a subject's identity.

Of course, there are many different types of modality in biometric recognition. In general, biometric systems can be classified as single modal systems and multiple modal systems, depending on how many modalities used in the systems.

2.2 Single Modal Systems

Currently, single modal systems have widely been used for person recognition. Some of them are based on physical traits, and the others utilize human behavioral cues. Figure 2.1 shows some single modal biometric systems, which are briefly described next.

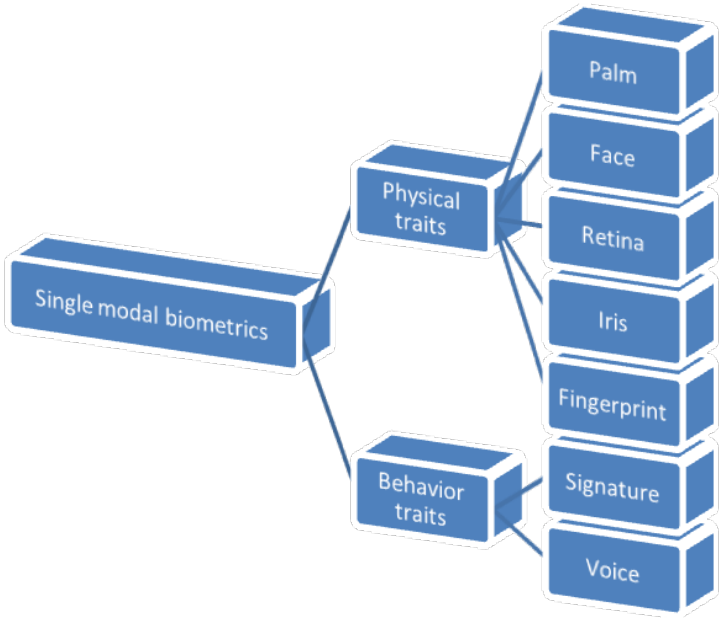


Figure 2.1 Biometrics classes

2.2.1 Face recognition

Face recognition analyzes facial characteristics. It requires a digital camera to capture one or more facial images of the subject for recognition. With a facial recognition system, one can measure unique features of ears, nose, eyes, and mouth from different individuals, and then match the features with those stored in the template of systems to recognize subjects under test. Popular face recognition applications include surveillance

at airports, major athletic events, and casinos. The technology involved has become relatively mature now, but it has shortcomings, especially when one attempts to identify individuals in different environmental settings involving light, pose, and background variations [17, 20, 23]. Also, some user-based influences must be taken into consideration, for example, mustache, hair, skin tone, facial expression, cosmetics, and surgery and glasses. Still there is a possibility that a fraudulent user could simply replace a photo of the authorized person's to obtain access permission. Some major vendors include Viisage Technology, Inc. and AcSys Biometrics Corporation.

2.2.2 Fingerprint recognition

The patterns of fingerprints can be found on a fingertip. Whorls, arches, loops, patterns of ridges, furrows and minutiae are the measurable minutiae features, which can be extracted from fingerprints. The matching process involves comparing the 2-D features with those in the template. There are a variety of approaches of fingerprint recognition, some of which can detect if a live finger is presented, and some cannot. A main advantage of fingerprint recognition is that it can keep a very low error rate. However, some people do not have distinctive fingerprints for verification and 15% of people cannot use their fingerprints due to wetness or dryness of fingers [33]. Also, an oily latent image left on scanner from previous user may cause problems [33]. Furthermore, there are also legal issues associated with fingerprints and many people may be unwilling to have their thumbprints documented. The most popular applications of fingerprint recognition are network security, physical access entry, criminal investigation, etc. So far, there are many vendors that make fingerprint scanners; one of the leaders in this area is Identix. Inc.

2.2.3 Hand recognition

Hand recognition measures and analyzes hand images to determine the identity of a subject under test. Specific measurements include location of joints, shape and size of palm. Hand recognition is relatively simple; therefore, such systems are inexpensive and easy to use. And there are not negative effects on its accuracy with individual anomalies, such as dry skin. In addition, it can be integrated with other biometric systems [32]. Another advantage of the technology is that it can accommodate a wide range of applications, including time and attendance recording, where it has been proved extremely popular. Since hand geometry is not very distinctive, it cannot be used to identify a subject from a very large population [33]. Further, hand geometry information is changeable during the growth period of children. A major vendor for this technology is Recognition Systems, Inc.

2.2.4 Iris recognition

Iris biometrics involves analyzing features found in the colored ring of tissue that surrounds the pupil. Complex iris patterns can contain many distinctive features such as ridges, crypts, rings, and freckles [33]. Undoubtedly, iris scanning is less intrusive than other eye-related biometrics [51]. A conventional camera element is employed to obtain iris information. It requires no close contact between user and camera. In addition, irises of identical twins are not same, even thought people can seldom identify them. Meanwhile, iris biometrics works well when people wear glasses. The most recent iris systems have become more user friendly and cost effective. However, it requests a careful balance of light, focus, resolution and contrast in order to extract features from images. Some popular applications for iris biometrics can be employee verification, and

immigration process at airports or seaports. A major vendor for iris recognition technology is Iridian Technologies, Inc.

2.2.5 Retina recognition

Retina biometrics analyzes the layer of blood vessels situated at the back of the eye [33]. This technique applies a low-intensity light source through an optical coupler to scan the unique and distinguish patterns of retina. The information contained in the blood vessel in retina would be difficult to spoof because an attacker cannot easily fake these patterns either by using fake eyes, a photograph, or a video. Retina biometrics can be quite accurate, but subject must be within a half- inch from the device. And he or she is required to keep his or her head and eye motionless when focusing on a small rotation point of green light [33]. Meanwhile, such technique is not convenient if subject wears glasses. So, it restricts some users with cataracts or eye problems. Retinal recognition is used for very high security access entry, such as nuclear and government installations.

2.2.6 Signature recognition

Signature can somehow indicate the distinct characteristics of that person. The signing features include speed and pressure as well as the finished signature's static shape [33]. Signature verification devices are reasonably accurate in operation, and obviously they can be used in the places where a signature is an accepted identifier, for example, transaction-related identity verification. This technique is a type of behavioral biometrics, so it changes over a period of time, and is influenced by physical and emotional conditions of that person. Furthermore, collecting samples for this biometrics also needs user’s cooperation.

2.2.7 Voice recognition

Voice authentication is not based on word but on voiceprint. The voice features are created by physical characteristics of a subject, such as vocal tracts, mouth, nasal cavities and lips. The pitch, tone, frequency, and volume of an individual's voice can uniquely identify a subject [37]. This authentication modality is the easiest one among all other biometrics, but, at the same time it is also potentially the least reliable, because voice is so easy to change. Another disadvantage of voice-based authentication systems is that voice can be easily duplicated (i.e. a tape recording).

2.2.8 DNA

DNA (Deoxyribonucleic acid) molecules are made of a long string of chemical building blocks. The sources of DNA are blood, semen, tissues, chemically treated tissues, hair roots, saliva, urine, etc. DNA has been used for many applications: forensic filed and organ donors matching. Benefits of DNA biometrics are that they can be obtained in everywhere of human cells and systems, and it has potential to achieve extremely high accuracy [33]. The downsides are that DNA samples are contaminated easily, and they are hard to control and store.

2.2.9 Summary of single modal systems

In summary, different single modal system extracts biometric data according to persons' physical or behavioral biometric traits or cues. Also, it is obvious that no single modal system is perfect to all of applications for person recognition in the real life. And there are some advantages and disadvantages to each single modal system.

Table 2.1 compares various single modal biometric technique based on hardware cost, ease of use, user acceptance, reliability and accuracy [26, 33, 41]. Table 2.2 compares those techniques according to their template sizes, the causes of errors and

major vendors. Table 2.3 shows advantages and disadvantages for various single modal systems.

Modal	Hardware cost	Ease of use	User acceptance	Reliability	Accuracy
Face	L*	M*	M	M	M
Fingerprint	L	H	L	H	H
Hand	H*	H	M	M	M
Iris	H	M	M	H	H
Retina	H	L	M	H	H
Signature	L	H	H	L	L
Voice	L	H	H	L	L
DNA	H	L	L	H	H

* H: high; M: medium; L: low

Table 2.1 Comparison of Various Biometrics

Modal	** Approx template size (bytes)	Causes of errors	Major vendors
Face	84~2k	Lighting, age, glasses, hair	Viisage, AcSys, …
Fingerprint	256~1.2k	Dryness, age, dirt	Identix, 123ID, …
Hand	9	Injury, age	Recognition Systems, …
Iris	256~512	Poor lighting	Iridian Technologies, …
Retina	96	Glasses	Retica System Inc. , ……
Signature	500~1k	Changing signature	Cyber Sign, SmartPen, …
Voice	70k~80k	Noise, sickness	Nuance,Keyware Tech., …
DNA	None	None	Siemens, …

Table 2.2 Comparison of single modal system (continued)

*** Approximate template sizes are cited from the website: www.simson.net/ref/2004/csg357/handouts/L10_biometrics.ppt*

Modal	Advantages	Disadvantages
Face	1.Not intrusive 2.Can be done from a distance	1.Affected by lighting, age, glasses, hair, and even plastic surgeries 2.User perceptions / civil liberty
Fingerprint	1.Easy to use 2.Small size of scanners 3.Non-intrusive 4.Large database available	1.Affected by cuts, dirt 2.Acquiring high-quality images 3.Not easy to enroll or use by the people with no or few minutia points
Hand	1.Easy to use 2.Non intrusive 3.Small template sizes	1.Lack of accuracy 2.Bigger size of the scanner 3.Fairly expensive 4.Hands injuries
Iris	1.Highly accurate 2.Not intrusive and hygienic	Not easy to scan the iris
Retina	1.Highly accurate	Intrusive and slow for enrollment and scanning
Signature	1.Lack of accuracy 2.Difficult to mimic the signing behavior	Changing signatures
Voice	1.Ability to use existing telephones 2.Low perceived invasiveness	1.Affected by noise and sickness 2.Not accurate
DNA	1.Accuracy 2.Uniqueness of evidences	1.DNA matching is not done in real-time 2.Contaminated easily 3.Civil liberty issues and public perception

Table 2.3 Comparison of single modal systems (continued)

2.3 Multiple Modal Systems

2.3.1 Multiple modal biometrics vs. single modal biometrics

Biometrics has been deployed in large-scale identification applications, which can range from border control to voter ID verification. Considering the range of different biometric authentication techniques, one may discover that performance of different biometric modalities varies for different individuals. For example, fingerprint identifies an individual from unique patterns of whorls and ridges on the surface of his or her own fingers, but there exist such scenarios in which some people have extremely faint fingerprints or no fingerprints at all. Another example is that iris authentication does not work very well on people who wear contacts or have a certain eye problems. From the tables above and section 2.1, some recognition errors are caused by the shortcomings of single modal systems. So, it is safe to say there are certain constraints about the single modal biometrics, and they are listed below [26, 33, 51]:

- Certain biometrics is vulnerable to noisy or bad data, such as dirty fingerprints and noisy voice records.
- Single modal biometrics is also inclined to interclass similarities in large population groups, for example, identical twins are not easy to be distinguished by face recognition system.
- Comparing to multiple modal systems, single modal biometrics is prone to spoofing, where the data can be imitated or forged.

Multiple modal biometric extract two or more biometrics and use fusion to produce a (hopefully) better recognition rate. Such technology can overcome restrictions and shortcomings from single modal systems and probably ensure lower failure rate for person recognition. The advantages of multiple modal biometrics are summarized below and shown in Fig.2.2. [26, 33, 51]

- A greater number of people can be enrolled into system by having an additional biometric available;
- Using multiple biometrics can deal with interclass similarity issues;
- When one biometric sample is unacceptable, the other can make up for it;
- It can solve data distortion problem;
- Comparing with multiple modal systems, single modal biometrics can be easily spoofed, but, by using multiple biometrics, even if one modality could be spoofed, the person would still have to be authenticated using the other biometric. Besides, the effort required for forging two or more biometrics is more difficult than forging one.

Figure 2.2 Advantages of multiple modal systems

However, while using multiple biometrics produces advantages, it also introduces disadvantages, which are shown in Fig.2.3.

Figure 2.3 Disadvantages of multiple modal biometrics

2.3.2 Multiple modal biometric fusions

As mentions above, multiple modal biometrics refers to the combination of different biometric traits. But how to effectively combine those biometric traits is a critical issue to such systems. Biometric fusion is a process of combining information from multiple biometric readings, either before, during or after a decision.

Information from those multiple modals can be fused at several levels: sensor, feature, score and decision level fusions [26, 33]. Fig. 2.4 shows various levels of fusion and the relevant fusion strategies.

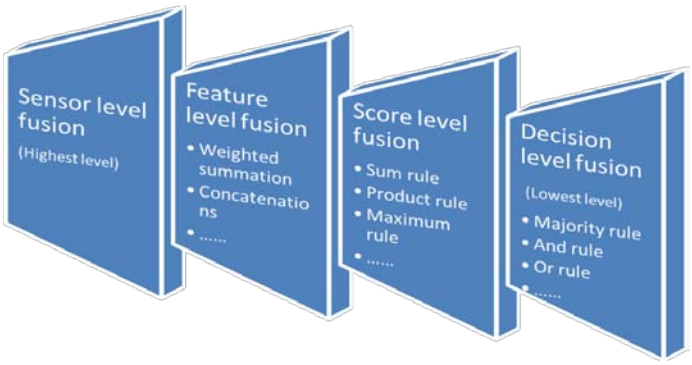


Figure 2.4 Various levels of multiple modal biometric fusion

2.3.3 Literature review

Multiple modal systems have been introduced for some time. A great amount of research work has been done for different multiple model systems, and better and better results have been achieved. In the literature, however, researchers focus more on score level and decision level fusion. Methods that use multiple types of biometric source for identification purposes (multi-modal biometric) are reviewed below. And the important aspects of these multiple modal studies are summarized in Tables 2.4.

Author	Year	Modals	Fusions	Size of tested database
Brunelli	1995	Face, voice	Score	89
Kittler	1998	Face, profile, voice	Score	37
Ben-Yacoub	1999	Face, voice	Score	37
Verlinde	1999	Face, profile, voice	Decision	37
Frischholz	2000	Face, voice, lip movement	Score	150
Ross	2001	Face, hand, fingerprint	Score	50
Wark	1999	Voice, lip movement	Score	37
Jourlin	1997	Voice, lip movement	Score	37
Luettin	1997	Voice, lip movement	Feature	12~37
Poh	2002	Face, voice	Score	30
Sanderson	2003	Partial face, voice	Score	12
Iwano	2003	Ear, voice	Score	38
Aleksc	2003	Video	Score	No report
Hazen	2003	Face, speech	Score	35

Table 2.4 Review of multiple modal systems

In 1995, Brunelli and Falavigna [4] proposed a method to recognize persons by combining audio and visual cues. The speaker recognition sub-system was based on Vector Quantization (VQ) of the acoustic parameter space and includes an adaptation phase of the codebooks to the test environment. A different method to perform speaker recognition, which made use of the Hidden Markov Model (HMM) technique and pitch information, was under investigation. Face Recognition was based on the comparison of facial features at the pixel level using a similarity measure based on the L1 norm. The integration of multiple classifiers was done at the hybrid rank/measurement fusion level, and the correct identification rate of the integrated system was 98%, which represented a significant improvement with respect to the rates of 88% and 91% provided by the speaker and face recognition system, respectively.

In 1998, Kittler et al. [29] combined three biometrics including frontal face, face profile and text-dependent voice from 37 subjects. For data fusion, they tested different rules, such as weighted summation, multiplication, minimum, and maximum rules, and the experimental comparison of various classifier combination schemes demonstrated that the combination rule developed under the most restrictive assumptions, the sum rule outperformed other classifier combinations schemes. A sensitivity analysis of the various schemes to estimation errors was carried out to show that this finding could be justified theoretically.

An integrated biometric authentication system using three modalities: a frontal face, text-dependent speech and text-independent speech were described by Ben-Yacoub et al. in 1999 [60]. The set of experts gave their opinion about the identity of an individual. The opinions of the experts could be combined to form a final decision by Support Vector

Machine (SVM) technique based on a binary classification method and the final results shown that their proposed method led to considerably higher performance.

In their work, Verlinde and Chollet [56] combined a frontal face, face profile and text-independent speech modalities, and used three simple classifiers. The first fusion method was a k-NN based classifier, used VQ to reduce the large number of imposter data points and gave good results but needed great amount of computing time. The second classifier was based on decision trees, but the results were slightly poorer. Finally the third method was a binary classifier based on the logistic regression, which required less computing time while achieved better classification results.

Frischholz and Dieckmann [14] proposed a multiple modal biometric system called BioID, which included face, speech, and lip movement. The system used physical features to check a person's identity and ensured much greater security than password and number systems. With its three modalities, BioID achieved much greater accuracy than single-feature systems. And the fusion was performed at the score level by the multiplication rule.

Ross [52] has investigated each of these methods for combining three biometric modalities: facial images, hand geometry and fingerprints. They found that the ‘Sum Rule’ method returned the best improvement over single modal systems. Their results showed that significant improvements could be made over single modal systems.

Wark et al. [58] fused the opinions from text-independent speech and lip movement modalities by the weighted summation rule. The features extracted from a speaker’s moving lips held speaker dependencies that were complementary with speech features. Their matching scores were fused by selecting correct weights to each sub-system’s score

and the results showed that the fusion of lip and speech information allowed for a highly robust speaker verification system that outperformed the performance of either sub-system. And another result was that the performance of the system decreased significantly whenever the noise level increased.

Jourlin et al. [27] integrated the text-dependent speech and lip movement modalities by the weighted summation rule. In their system, a lip tracker was used to extract visual information from the speaking face which provided shape and intensity features. And they described an approach for normalizing and mapping different modalities onto a common confidence interval, and also presented a method for integrating the scores of multiple classifiers. Verification experiments were reported for the individual modalities and for the combined classifier, and indicated that the integrated system outperformed each sub-system and reduced the error rate of the acoustic sub-system.

Luettin [37] attempted to combine the speech and lip movement features by feature vector concatenation. A speech-reading (lip-reading) system was presented which modeled these features by Gaussian distributions and their temporal dependencies by HMM. The models were trained using the EM-algorithm and speech recognition was performed based on maximum posterior probability classification. It was shown that, besides speech information, the recovered model parameters also contained person dependent information. Talking persons were represented by spatial-temporal models that described the appearance of the articulators and their temporal changes during speech production. The proposed methods were evaluated on an isolated database of 12 subjects, and again on a database of 37 subjects. The techniques were found to achieve good

performance. But the system performance in the text-dependent condition was not significantly improved.

"Hybrid multiple biometrics" was described by Poh et al. in 2002 [46]. The multiple samples were collected from multiple biometrics. In their work, five samples for each of face and voice of 30 subjects were collected. The results showed that 1) as the number of samples was increased, the accuracy improvement rate in face was faster than that for speech; 2) the improvement rate by the multiple biometrics was faster than the multiple samples' one.

Sanderson et al. [53] tested an AV system by using partial face images in 2003. The Bayesian Maximum a Posteriori (MAP) approach was applied for speech recognition. Two HMMs were used for synchronous alignment to retrieve the best path through the models. And the eigenface method was used for face recognition. In the fusion process, an adaptive weight was considered based on the recognition accuracy rate of individual modality. The results showed that a combined method yielded better performance over individual biometrics.

A bi-modal biometrics system using a person's ear and speech was shown by Iwano et al [25], and the experimental results from totally 38 subjects showed that the accuracy of the bi-model system became more robust to additive white noise to speech signals than that of the single speech system. In the process, the speech features were modeled by a HMM and ear features obtained by the Principle Component Analysis (PCA), and they were then modeled with GMM. Finally, the product of log-likelihood of the posterior probabilities produced matching scores.

Aleksc et al presented an audio and video person recognition system under the score fusion level [1]. The visual and audio features from videos were modeled by facial animation parameters (FAP) and HMM separately. FAP could examine the facial movement while the observed person was speaking. Their result showed that the bi-modal system out-performed the single speech recognition system.

Another AV system was described by Hazen [16]. It was text-dependent AV system used in mobile environments. Speech recognition was based on a spoken utterance vs. a prompted utterance, and face recognition was based on the SVM classifier. Once SVM was trained, a test image was ranked based on selected *n* normalized distances from the zero-mean decision hyper-plane. And the recognition rate in this AV system, which included 35 subjects, was claimed better than a pure speech recognition system.

3 FACE RECOGNITION

3.1 Introduction

Although human faces are very similar from person to person, human beings often recognize one another by unique facial characteristics. Those characteristics include the dimensions, proportions and physical attributes of a person's face [33], for example, 1) distances among the eyes, nose, mouth, and jaw edges; 2) the outlines, sizes and shapes of eyes, mouth, nose and eyes as well as the area surrounding the cheekbones. Automatic facial recognition is based on this phenomenon. It will measure and analyze the overall structure, shape and proportions of face.

Varying lighting conditions, facial expressions, poses and orientations can complicate the face recognition task, making it one of the most difficult problems in biometrics [36]. Despite the problems listed above and the fact that other recognition methods (such as fingerprints, or iris scans) can be more accurate, face recognition is the most successful form of human surveillance. It has been a major focus of biometric research due to 1) its non-invasive nature; and 2) it is people's primary method of person identification. Interest in face recognition is being triggered by availability and low cost of hardware, installment of increasing number of video cameras in many areas, and the noninvasive aspect of facial recognition systems.

Although face recognition is still in research and development phase, several commercial systems are currently available and more than a dozen research

organizations, such as Harvard University and the MIT Media Lab, are working on it. Although it is hard to say how well the commercial systems are, three systems (refer to their websites), Visionics, Viisage, and Miros, seem to be the current market leaders in this area, and they are briefly introduced in the following:

- Visionics' FaceIt face recognition software is based on the local feature analysis algorithm developed at Rockefeller University. FaceIt is now being incorporated into a Close Circuit Television (CCTV) anti-crime system called `Mandrake' in United Kingdom.
- Viisage, another leading face recognition company, uses the eigenface-based recognition algorithm developed at the MIT Media Laboratory. Their system is used in conjunction with identification cards (e.g., driver's licenses and similar government ID cards) in many US states and several developing nations.
- Miros uses neural network technology for their TrueFace face recognition software. TrueFace is used by Mr. Payroll for their cashing system, and has been deployed at casinos and similar sites in many states.

Face recognition with high speed and robust recognition accuracy presents a significant challenge in this area, thus, there are many researches done for it. Research on face recognition goes back to the earliest days of AI and computer vision. Here we will focus on the early efforts that had the greatest impact and those current systems that are in widespread use, such as Eigenface [42, 55], statistical model, Neural Network (NN) [48], Dynamic Link Architectures (DLA) [34], Fisher Linear Discriminant Model (FLD), Hidden Markov models (HMM) and Gabor wavelets. For the detailed survey of face

analysis techniques, the reader is referred to many internet free tutorial papers. The following will give a short survey about this technology.

In 1989, Kohonen [31] demonstrated that a simple neural net could perform face recognition for aligned and normalized face images. The type of network he employed computed a face description by approximating the eigenvectors of the face image's autocorrelation matrix; these eigenvectors are now known as “eigenfaces”.

Kohonen's system was not a practical success. In following years many researchers tried face recognition schemes based on edges, inter-feature distances, and other neural network approaches. Kirby and Sirovich (1990) [28] later introduced an algebraic manipulation that made it easy to directly calculate the eigenfaces. Turk and Pentland (1991) [55] then demonstrated that the residual error when coding using the eigenfaces could be used both to detect faces in cluttered natural imagery, and to determine the precise location and scale of faces in an image. They demonstrated that by coupling this method for detecting and localizing faces with eigenface recognition method, one could achieve reliable, real-time recognition of faces in a minimally constrained environment.

Recent approaches also include Gabor wavelet method, whose kernels are similar to the two-dimensional receptive field profiles of the mammalian cortical simple cells, capturing salient visual properties such as spatial localization, orientation selectivity and spatial frequency characteristics [17, 36, 38, 44]. Because of this, Gabor wavelet is often used in image representation. Some work has been done to apply Gabor Wavelet Transform (GWT) for face recognition. The results reported in the literature demonstrated that Gabor wavelet representation of face images will be robust to variations due to illumination, viewing direction and facial expression changes as well as

poses [17, 20, 36, 38, 44]. Lades et al. [34] were among the first to use the Gabor wavelet for face recognition using a DLA model. Donato et al. [12] illustrated that the Gabor wavelet representation gives better experimental results than other techniques, in terms of classifying facial actions. Based on the 2-D Gabor wavelet representation and the labeled elastic graph matching, Lyons et al. [38] proposed an algorithm for two-class categorization of gender, race and facial expression. In [36], Liu proposed the Gabor-Fisher Classifier (GFC).

As talked before, in the real person recognition systems, the computational cost and biometric data storage size as well as the recognition rate are the most important issues. The motivation of developing the PGE algorithm [20] is that it can keep a lower computational cost and smaller data space; meanwhile, it also can obtain the better recognition result. In this paper, the multi-resolution Pyramidal Gabor Wavelet scheme (PGW) [20] is applied to face recognition, which uses 1-D filter masks in the spatial domain instead of 2-D filtering operations. This implementation is proven faster and more flexible than a Fourier implementation that a Gabor-based face recognition method normally uses. Furthermore, this paper introduces the PGE algorithm, which implements the PGW and Eigenface methods to classify face images. The algorithm analysis shows that it has the potential of achieving even faster computational speed and the use of less computer memory than the classic 2-D Gabor wavelet based face recognition schemes. Meanwhile, the PGE algorithm overcomes weak facial feature representation, in terms of correlation, of the Eigenface method, due to its sensitivity to input image deformations caused by, among other things, lighting and pose variations.

The remainder of this chapter is organized as follows: Section 3.2 briefly describes the Eigenface method, for basic understanding of the dissertation. Section 3.3 introduces the PGW algorithm. The PGE algorithm and the analysis of its computational cost are presented in Section 3.4. Experimental results of the PGE procedure are given in Section 3.5. Section 3.6 will end the chapter with the concluding remarks.

3.2 Eigenface

Eigenface is used to extract a subspace where the variance is maximized, or the reconstruction error is minimized, by finding the basis vectors of a low-dimensional subspace, using second-order statistics, as a set of orthogonal eigenvectors [20]. Using only the "best" basis vectors with the largest eigenvalue can describe the distribution of face images in the image space and form eigenspace, thereby reducing the dimension for a face image and producing uncorrelated feature vectors. The Eigenface algorithm can be divided into two stages: 1) training stage, and 2) recognition stage.

In the first stage, the eigenface matrix is obtained. Let Γ be training sets consisting of M face images $\{\Gamma_1, \Gamma_2, ..., \Gamma_M\}$, where Γ_i is a $r \times c$ matrix, with r and c denoting the numbers of rows and columns for each image separately. The average face of training sets is defined by (3.1), and each face differs from the average face by (3.2).

$$\Psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma_i \tag{3.1}$$

$$\Phi_i = \Gamma_i - \Psi \tag{3.2}$$

Each 2-D difference image can then be converted into a vector $\vec{\chi}$ of length $\rho \times 1$, and construct a $\rho \times M$ matrix X where ρ is equal to the product of r and c. The eigenvalues and eigenvectors are obtained from covariance matrix (3.3). To reduce the

computational complexity, *C* is replaced with inner product *R* by (3.4). An $M \times M$ eigenvector matrix Q of *R* is given by (3.5).

$$C = \frac{1}{M}\sum_{i=1}^{M} \chi_i \chi_i^T = \frac{1}{M} XX^T \tag{3.3}$$

$$R = \frac{1}{M} X^T X \tag{3.4}$$

$$E = XQ \tag{3.5}$$

The M^{th} eigenface can be ignored since it was derived from a product operation that included the M^{th} column of matrix Q, which is a zero vector. Then, a new eigenface matrix, holding the significant eigenfaces, is defined as E_s, of $\rho \times (M-1)$ dimensions. In order to project *X*, the operation is applied by (3.6).

$$\overset{\cdots}{X} = E_s{}^T X \tag{3.6}$$

The second stage of the Eigenface algorithm is processed to classify and possibly identify test images with one or some of the training images. Assume a test image *Y* of size $r \times c$. The test difference vector can be found by applying equation (3.7). Φ_Y is converted into a vector $\vec{\upsilon}$, then projected into the eigenspace by (3.8).

$$\Phi_Y = Y - \Psi \tag{3.7}$$

$$\overset{\cdots}{\upsilon} = E_s{}^T \upsilon \tag{3.8}$$

Finally the test image are classified and identified by calculating the distance between the projected test image, $\overset{\cdots}{\upsilon}$, and the projected training images contained in $\overset{\cdots}{X}$.

The drawback of Eigenface is that it is a global approach and only uses second-order statistics of face image, which may cause problems in robustness and generality. In

an eigenspace, there are some unwanted variations [55]. Accordingly, the features produced may not necessarily be good for discrimination among classes. Thus, Eigenface is sub-optimal in terms of classification. Related research [23, 42] has showed that Eigenface is sensitive to variability due to expression, pose, and lighting condition.

3.3 Pyramidal Gabor Wavelets

In image processing and computer vision, multi-scale modeling has attracted increasing interest. Pyramidal Gabor wavelet transform consists of subtracting from the original image its low-pass filtered version (obtained in the first level of the pyramid before down sampling), together with the highest frequency Gabor channels.

Gabor functions are not orthogonal, so the classic Gabor expansion is computationally expensive. The problem can be partially solved by a redundant, multi-scale filtering operation. Oscar et al. [44] proposed a method of multi-scale image representation based on Gabor functions, PGW, which is an optimized spatial implementation. It applies separable 1-D filter masks, with small size in the spatial domain, to get Gabor features without using the Fourier and inverse transforms. Therefore, it is faster than Fourier transform. Meanwhile, it can reduce the amount of computer data storage. The Gabor Wavelet function is defined as:

$$\begin{aligned} g(x,y) = \exp(-\pi((x-x_0)^2/\alpha^2 + (y-y_0)^2/\beta^2)) \\ .\exp(-i2\pi(\mu_0(x-x_0) + \nu_0(y-y_0))) \end{aligned} \tag{3.9}$$

where (x_0, y_0) specify wavelet position, (α, β) are the effective width and length, and (μ_0, ν_0) is a modulation wave-vector, which can be interpreted in polar coordinates as spatial frequency $f_0 = \sqrt{{\mu_0}^2 + {\nu_0}^2}$ and orientation $\theta_0 = \arctan(\nu_0 / \mu_0)$.

If the equation (3.9) is tuned to the frequency f_0, orientation θ_0, and centered at the origin ($x_0 = 0$, $y_0 = 0$), it will be shown as (3.10), which can be rewritten as (3.11).

$$g_{0,0,f_0,\theta_0}(x,y) = \exp(-\pi a^2(x^2 + y^2)) \cdot \exp(i2\pi f_0(x.\cos\theta_0 + y\sin\theta_0)) \tag{3.10}$$

$$g_{0,0,f_0,\theta_0}(x,y) = \exp(-\pi a^2 x^2).\exp(-\pi a^2 y^2) \cdot (\cos(2\pi f_0 x.\cos\theta_0) + i\sin(2\pi f_0 y.\sin\theta_0)) \tag{3.11}$$

where a determines the spatial frequency bandwidth and set $a = 1/\alpha = 1/\beta$.

Equation (3.11) can be defined as a sum of two separable filters:

$$\begin{aligned} R_{0,0,f_0,\theta_0,p=0}(x,y) &= [g_x \cdot \cos(2\pi f_0 x\cos\theta_0)] \cdot [g_y \cdot \cos(2\pi f_0 y\sin\theta_0)] \\ &\quad -[g_x \cdot \sin(2\pi f_0 x\cos\theta_0)] \cdot [g_y \cdot \sin(2\pi f_0 y\sin\theta_0)] \\ R_{0,0,f_0,\theta_0,p=1}(x,y) &= [g_x \cdot \sin(2\pi f_0 x\cos\theta_0)] \cdot [g_y \cdot \cos(2\pi f_0 y\sin\theta_0)] \\ &\quad -[g_x \cdot \cos(2\pi f_0 x\cos\theta_0)] \cdot [g_y \cdot \sin(2\pi f_0 y\sin\theta_0)] \end{aligned} \tag{3.12}$$

where g_x and g_y are 1-D Gaussian function, $g_x = \exp(-\pi a x^2)$ and $a = (3\sqrt{\ln 2/\pi})^{-1} f_0$.

Each block in (3.12) is a 1-D filtering operation. By performing a constrained least squares minimization of the error of frequency response, four 1-D Gabor masks can be obtained. It changes the traditional 2-D Gabor filtering operation into a set of 1-D operations. If θ_0 is 0^0, 45^0, 90^0, and 135^0 respectively, these filters can be used to get 4 orientations and 2 parities of one level. The filter masks used in PGW have been given in Table 3.1 [44].

Filter	Mask
θ=0^0 or 90^0, p=0	0, 17, 0, -62, 0, 90, 0, -62, 0, 17, 0
θ=0^0 or 90^0, p=1	-8, 0, 37, 0, -82, 0, 82, 0, -37, 0, 8
θ=45^0 or 135^0, p=0	3, -5, -27, -27, 25, 62, 25, -27, -27, -5, 3
θ=45^0 or 135^0, p=1	4, 13, 5, -34, -52, 0, 52, 34, -5, -13, -4
Gaussian (X or Y)	4, 9, 19, 31, 41, 45, 41, 31, 19, 9, 4

Table 3.1 Filter masks

The block diagram for 1-D operations is shown in Fig. 3.1.

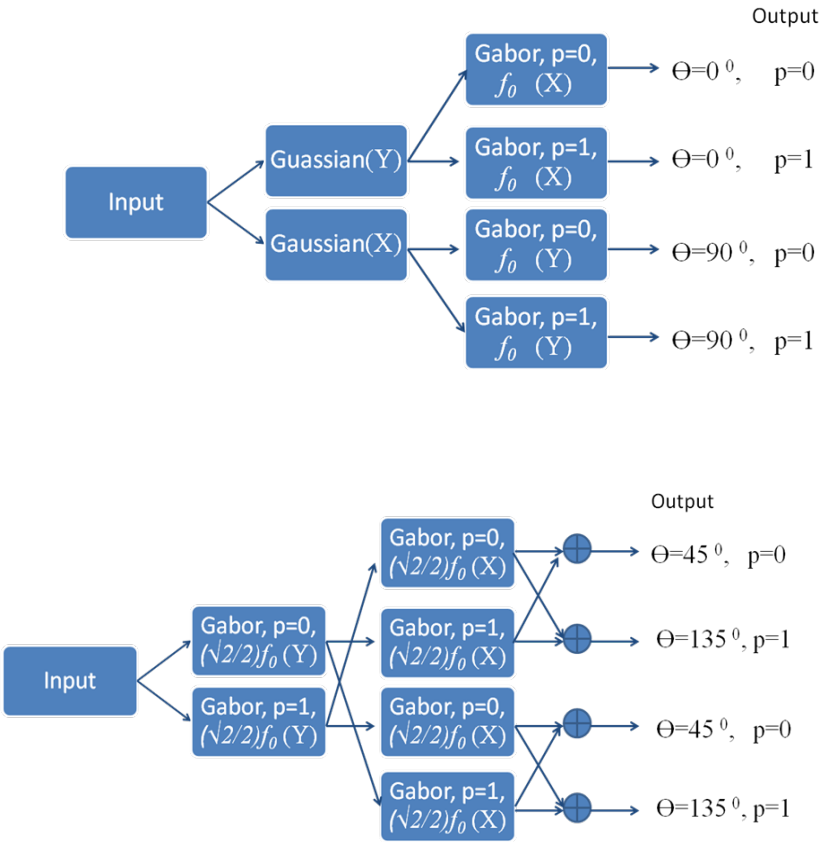


Figure 3.1 PGW filtering operation in one level

3.4 PGE algorithm and analysis

3.4.1 PGE Algorithm

Gabor wavelets, or Gabor functions, have been found suitable for face image decomposition and representation for their biological relevance [20, 36]. Since Gabor functions are not orthogonal and have dual basis functions, they are computationally expensive [61]. It is the main reason that we apply pyramidal procedure to PGE method.

The new procedure has the following advantages:

- It maximizes joint localization in both spatial and frequency domains [44];
- It exhibits strong characteristics of spatial locality, as well as scale and orientation selectivity;
- It is not sensitive to illumination and rotation of images;
- It can be expressed as a sum of two separable filters, which allows the use of 1-D filter masks in the spatial domain to reduce the computational cost.

The classic GWT usually involves 2-D filtering operations. Previous work on face recognition using GWT normally has the following steps:

- Transform Gabor functions and face images from the spatial domain to the frequency domain *via* Fourier transform [36, 38, 61];
- Multiplex them to obtain the output of Gabor features in frequency domain;
- Apply inverse Fourier transform to get Gabor features in spatial domain;
- Construct the feature vectors;
- Applies PCA, DLA, or FLD to further compress the GWT results.

Those methods require a 2-D Fourier transform and inverse transform to Gabor functions and face images. On the other hand, the proposed PGE algorithm uses only small (11-tap) 1-D filter masks, resulting in a spatial domain implementation. This is much faster than other 2-D Gabor-based schemes that employ the Fourier and inverse transforms. Therefore, the procedure is not as computationally expensive, in terms of memory and CPU time, as other methods.

The proposed PGE algorithm consists of training and recognition stages.

During the training stage, the robust Gabor features of the training face sets are obtained by applying the PGW procedure to the training images in the four levels and four orientations. To encompass the Gabor features for every training face, the rows of all its feature representations can be concatenated to derive an augmented feature representation. The augmented feature representations for all training face images are normalized to zero mean and unit variance. The Eigenface method transforms them into the eigenspace, which is able to optimally classify individual facial representations.

The second stage of the PGE algorithm performs the PGW to extract the Gabor features of the testing face sets, and then projects the test difference vectors represented by (3.7) into the eigenspace by (3.8). Finally the test images are classified by calculating the distance between the projected test image and the projected training images.

From the PGE algorithm, it is known that Gabor wavelet representation facilitates recognition without correspondence, because it captures the local structure corresponding to spatial frequency, spatial localization, and orientation selectivity. As a result, the Gabor wavelet representation of face images is robust while dealing with the variations caused by illumination condition, viewing direction, poses, facial expression changes and

disguises. This kind of benefit will overcome the weak facial feature representation of Eigenface, in terms of correlation, due to the sensitivity of Eigenface to face image deformations caused by illumination and pose variations. Moreover, PGE shows improved discrimination ability since Gabor responses transfer to the space constructed by the principal components [20, 44].

The following steps summarize the PGE algorithm:

1) Acquire the training face set and testing face set;
2) Implement PGW in four levels and four orientations to the training face set and the testing face set;
3) Extract Gabor feature vectors from step 2);
4) Normalize the Gabor feature vectors and get the augmented feature representations;
5) Apply Eigenface to the augmented feature representations of the training face set, and construct eigenface matrix;
6) Project the extracted features of the testing face set to the eigenspace, compute the distances for all the projections, and classify the faces.

3.4.2 Algorithm Analysis

The storage requirement of filter responses related to this algorithm is less than the one related to the classic algorithm based on 2-D Gabor wavelet. The pyramidal Gabor wavelet in the PGE algorithm applies only small-size 1-D filter masks to obtain four orientations and two parities of one level in the spatial domain. Also, the implementation only has to keep in memory a few coefficients corresponding to the 1D convolution masks [44]. In contrast, a 2-D Fourier transform of an $N \times N$ image will be of

size $N \times N$. In performing an N point's 2-D Fourier transform to the Gabor wavelets, the number of data points kept in the memory is also $N \times N$. In order to implement multiplication in the frequency domain between the image and the Gabor wavelet, the memory size will be $2 \times N \times N$. That is, the amount of memory needed to store the filter responses in PGW is much smaller than a Fourier implementation of 2-D Gabor filtering because Fourier implementation needs keep in memory the frequency responses of highest frequency for all images. This requires a huge amount of data storage.

As to the storage amount required for the extracted Gabor features when, for example, implementing four orientations and four levels to an image of size 256×256, the pyramidal Gabor features for the four level image decompositions are 256×256, 128×128, 64×64, and 32×32 respectively, the memory size of the Gabor feature vectors for the four orientations in PGE is $4 \times (256 \times 256 + 128 \times 128 + 64 \times 64 + 32 \times 32) = 348{,}160$ bytes. This becomes $4 \times [\, 4 \times (256 \times 256) \,] = 1{,}048{,}576$ bytes in some general 2-D Gabor-based schemes, which means their Gabor feature storage amounts will be three times that of the PGE algorithm during the Gabor feature extraction procedure.

Another important issue is the computational cost related to image dimensions of the algorithm [18]. Due to 1-D filter operation in PGW, to an image with the size of $N \times N$, the computational cost of PGW is $O(N^2)$ [42]. The cost of Eigenface is mostly from the process of determining the correlation matrix R, its cost related with the image size is $O(N^2)$ without considering the number of training face images [42]. Finally, the cost of PGE algorithm is $O(N^2)$. But previous work on face recognition using GWT usually has to process 2-D Fourier implementation, and the complexity of Fourier

analysis is $O(N^2 \log_2 N)$. That will bring the total cost of this type of recognition to $O(N^2 \log_2 N)$. For a database with an image size of 256×256, the computational cost of the classic 2-D Gabor-based methods is eight times that of PGE algorithm.

3.5 Experiment

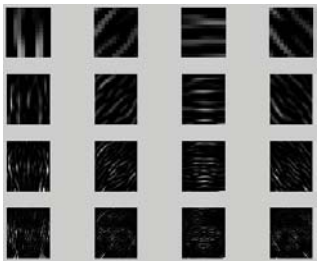
The feasibility and performance of the proposed PGE algorithm was verified by using the standard AT&T database, which contains 400 images of 40 subjects. Every subject has 10 face images. The size of each image is 92×112 pixels, with 256 gray levels per pixel. Fig. 3.2 shows sample face images from the database. It shows face images with variation in poses, expression, viewing direction, etc., in the database.

Figure 3.2 Some samples face images in the AT&T database

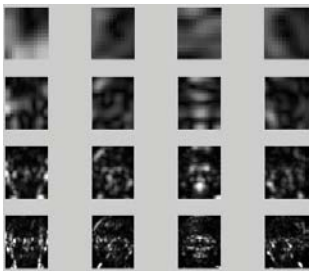
In the following experiments, the training set was constructed by randomly selecting five images for each subject. The testing set consisted of the relative rest of the database. There was no overlap between the training and testing face sets. Some images in the testing set are shown in Fig. 3.3.

Figure 3.3 Samples of the testing face images

The real part and magnitude part of the extracted Gabor features of one face image in the training face set of the AT&T face database are shown in Fig. 3.4a and 3.4b, respectively.



(a)



(b)

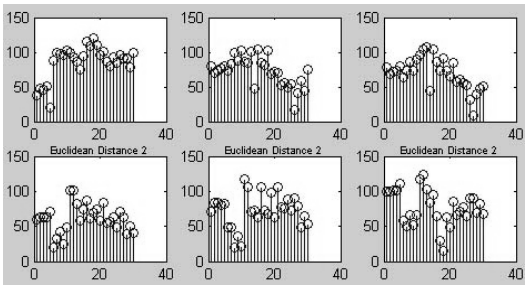
Figure 3.4 Gabor features representations of one sample image:

(a) the real part of the representation; (b) the magnitude of the representation

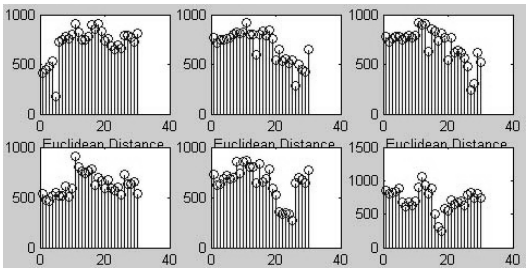
In order to clearly present the comparison results between the Eigenface and PGE methods in this paper, partial training images from the training set were selected (Fig 3.5a). Meanwhile, Fig 3.5b and 3.5c are the Euclidean distances after implementing the PGE algorithm and stand-alone Eigenface method in this partial training / testing face set respectively. It shows that the Eigenface method cannot recognize fourth and fifth images in Fig 3.5. Therefore, the recognition rate of Eigenface procedure is lower than that of the PGE algorithm. The reason for this is that the Gabor features in PGE is robust when

dealing with the variations caused by illumination condition, viewing direction, poses, facial expression changes and disguises. In contrast, Eigenface is very sensitive to face image deformations caused by illumination and contrast variations, and rotations. In fact, the PGE algorithm achieves better recognition accuracy using the available face database.

(a)



(b)



(c)

Figure 3.5 Euclidean distances of Fig.3:

(a) some training faces, (b) results of PGE algorithm, (c) results of Eigenface.

To any recognition technique, computational cost and data storage are two critical issues, in addition to recognition rate. The PGE algorithm not only can achieve a better recognition rate, it can keep the computational cost and storage space lower than the Eigenface and traditional Gabor wavelet based methods. Table 3.2 shows a comparison of recognition rates, computational costs, and storage required for the three methods. It shows that a performance of 97.0%, 95.5%, and 87.5% recognition rates were obtained by PGE algorithm, 2-D Gabor wavelet method, and stand-alone Eigenface method, respectively. However, the relevant computational cost and the storage amount of the Gabor features in the classic 2-D Gabor wavelet based method are about two times and seven times higher, respectively, than the ones in PGE algorithm, yet the PGE algorithm has a better recognition rate. In other words, face recognition using the proposed PGE algorithm results in significantly lower computational complexity than the 2-D Gabor wavelet method while a comparable recognition rate is maintained. Meanwhile, both methods outperform the stand-alone Eigneface method in terms of recognition rate.

Method	Recognition rate	Computational cost	Gabor feature (Bytes)
Eigenface	87.5%	$O(N^2)$	None
2-D Gabor	95%	$O(N^2 \log_2 N)$	164,864
PGE	97%	$O(N^2)$	54,768

Table 3.2 Comparison among PGE, Eigenface and classic 2-D Gabor based methods

3.6 Summary

In this chapter, the PGE algorithm has been proposed for face recognition. The Pyramidal Gabor wavelet in the PGE algorithm exhibits the characteristics of strong spatial locality, scale and orientation selectivity, and extraction of robust Gabor facial features. This solves the variation problems caused by illumination condition, viewing direction, pose, facial expression change and disguise, which the Eigenface method cannot overcome. Since the algorithm applies only small-size 1-D filter masks to obtain the Gabor features in 4 orientations and 4 levels in the spatial domain and the implementation only has to keep in memory a few coefficients corresponding to the 1-D convolution masks, its implementation is much faster than the classic 2-D Gabor-based methods via Fourier transform and inverse transform. The extracted Gabor features are further processed by the Eigenface method to reduce data redundancy. Furthermore, any technique concerning human recognition has to carefully consider the computational cost and data storage issues. The analysis has shown that the cost of the algorithm and the storage requirement of the Gabor features in the PGE algorithm are significantly lower than the classic 2-D Gabor wavelet based methods, while maintaining a better recognition rate, as shown with AT&T database. The performance with the original image and scaling components at various levels at the 92×112 , 46×56 , 23×28 and 12×14 resolutions, is much more beneficial in terms of computational cost and data storage requirement. In short, PGE algorithm produces superior performance for face recognition.

4 VOICE RECOGNITION

4.1 Introduction

Many people are familiar with voice communication and feel comfortable with it. We are used to this identification process in our everyday lives. That is what highlights the notion of using an individual's voice to uniquely identify what they say they are.

Automatic speaker recognition is the process of automatically recognizing who is speaking based on specific information/features included in speech signals by machines. It is based on voiceprints instead of word recognition. But the questions are how we can recognize the voices of those familiar to us and what will be voiceprints in humans' voice. According to the linguistic research [15, 27, 47], speech carries person dependent information due to the largely unique configuration of vocal tract and vocal folds for each person. Therefore, one can uniquely identify person by using the pitch, timbre, acoustic spectrum, accent, and volume of an individual's voice. In another word, one can recognize voices not only by counting on a huge amount of inter-related features (such as basic "sound"), but also by a characteristic accent or turn of phrase. Depending on context and acoustic conditions, certain features may be particularly valuable to recognize the melody of a speaker's voice.

But there are some downsides of voice-based authentication systems. For example, voice, as one biometric characteristics, can be easily duplicated (i.e. a tape recording of a legitimate user). That means voice biometrics may be easily to spoof by an attacker who

may record legitimate user's voice in some ways. Another example is that subject under test has caught a cold and has been denied to access some personal information because his or her voice has been dramatically changed. In addition, background noise affects the performance of voice systems, too [33].

Speaker recognition has been an active research area for many years, and made great progress in theory and application so far. This technique can be classified into speaker identification and verification systems. Speaker identification means automatically recognizing who is speaking amongst a set of known speakers. Speaker verification is used to accept or reject the identity claim of a speaker. Meanwhile, speaker recognition systems could be either *text-dependent* (the same texts, passwords or numbers are spoken during enrollment and testing periods) or *text-independent* (speaker can say whatever he or she want to say during enrollment and testing periods). Text-independent systems are more commercially attractive than text-dependent one because it is harder to mimic an unknown phrase than a known one, and such systems will be more flexible, convenient and friendly to users.

Currently, speaker recognition has been used to verify speaker's identity and control access to restricted services or areas, such as banking by phone, surveillance, forensic work, and security control for confidential information.

The general approach to speaker recognition consists of the following steps (see Fig. 4.1) [3, 5, 47]:

- Digital speech data acquisition,
- Feature extraction,
- Pattern matching,

- Decision (or determine the speaker).

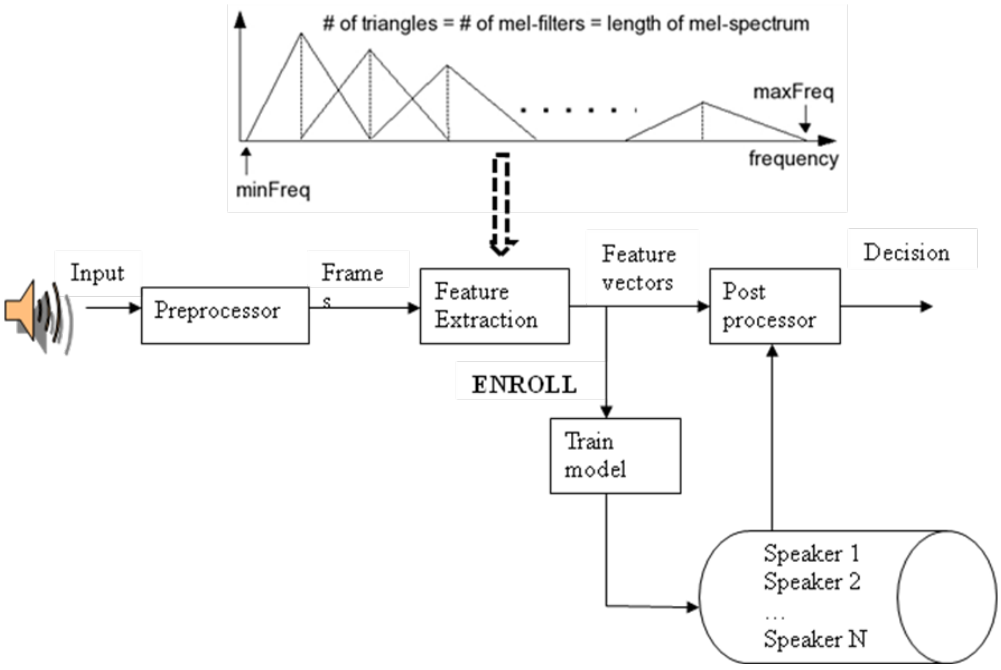


Figure 4.1 Modular of speaker recognition

Feature extraction maps each interval of speech to a feature space. Many forms of pattern matching and corresponding models are possible, which include dynamic time warping (DTW), VQ, GMM, HMM, artificial neural networks, etc [5].

The outline of this chapter is as following: Section 4.2 presents MFCC feature extraction method, VQ and GMM classifier; Section 4.3 shows the experiment results and conclusions will be made in Section 4.4.

4.2 Text-independent Speaker Recognition

Speaker recognition consists of transforming the original speech signal to a set of feature vectors. Those feature vectors are new representation, which is more compact, less redundant and more suitable for statistical modeling to recognize subject under test. How to obtain such feature representation is a key issue in audio biometrics. It is known

that speech signals are non-stationary [3, 33]. That means we cannot use traditional Fourier method to handle the whole speech signal. But their short-term segments in the whole speech can be considered to be stationary [33], which means that classical signal processing techniques such as spectral and cepstral analysis, can be applied to short segments of speech on frame by frame basis. And so far, many researches have been done. Among them, most popular one employs the information from mel filterbanks in form of a short-time Fourier spectrum represented by Mel Frequency Cepstral Coefficients (MFCCs) [5, 18]. In this section, the operation of MFCCs is outlined.

Considering the amount of feature sets for each subject, the MFCCs have to be compressed before performing feature fusion in AV system. Vector Quantization (VQ) [35] is one of the popular algorithms to be used for this purpose and will also be discussed further.

After obtaining the compressed feature vectors, classification by GMM is introduced. And estimation method, EM, is also described in this section.

4.2.1 Audio Feature Extraction

Fig. 9 shows a preprocessor to obtain audio frames that are used by MFCC feature extraction component in later stage. The task of high-pass filter (HPF) depicted in Fig. 9 is to enhance high frequencies of audio signal, which are generally attenuated during audio recording process.

Figure 4.2 Preprocessor of audio signal

The analysis of audio signal is done locally by applying for a window whose duration in time is shorter than the whole signal, then moved further frame by frame until the end of audio signal. Each application of window to a portion of audio signal provides a spectral vector after implementing FFT. Two values have to be chosen: the length of window and the shift between two consecutive windows. The length of window is set as 20 ms which corresponds to the average duration. And the shift value is 10ms that is chosen to be the overlap between two consecutive windows [3]. The Hamming and Hanning windows are the most used in speaker recognition in order to reduce some side effects. After preprocessing, the length of speech frame is 20ms with an overlap of 10ms.

After preprocessing, signals will be employed by FFT to get their power spectrum, which presents a lot of fluctuations. The only interested part of spectrum is its envelope. To further smooth the spectrum and get its envelope, a filter bank will be applied.

A filter bank is a set of band pass filters that span the entire audible frequency and isolate different frequency components in audio signal. The filters' shapes and frequency locations (including left frequency, central frequency, and right frequency) define filter banks. Among filter banks, the scale of Mel filter banks is most similar to the frequency scale of human ears [33]. Mel filter banks consist of a number of overlapping triangular filters with different center frequencies and bandwidths. Fig. 10 shows Mel filter banks. And the mapping from the actual frequency f to Mel frequency f_{Mel} is defined as,

$$f_{Mel} = 2595 \times \log(1 + f / 700) \tag{4.1}$$

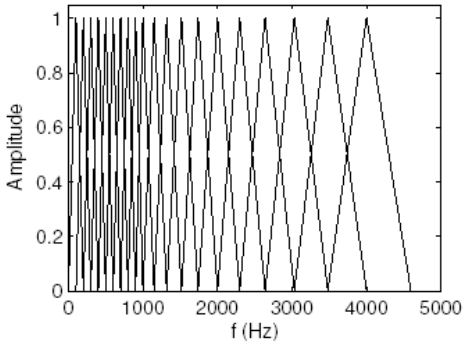


Figure 4.3 Mel filter banks

After applying a bank of filters to each input spectrum, output of these filters, called Mel spectrum, forms a spectral envelope that has enhanced those more important frequencies and reduced the spectrum dimension to the number of filters in filter banks. After that, Discrete Cosine Transform (DCT) is applied to obtain the cepstral coefficients. Fig.4.4 shows MFCCs feature extraction procedure used in this chapter.

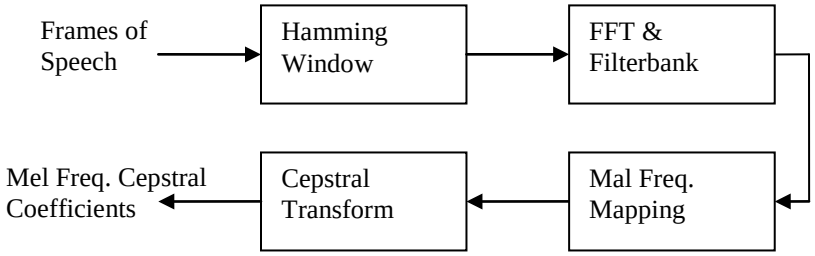


Figure 4.4 Procedures of MFCC

4.2.2 Vector Quantization

Vector quantization (VQ) is one of compression methods used in many applications such as image compression, voice compression, and voice recognition [3]. A vector quantizer maps *k-dimensional* vectors in the vector space $\Re^k$ into a finite set of vectors $Y = \{y_i: i = 1, 2... N\}$[35]. Each vector y_i *is* called a codeword, and codebook is

constructed by the set of all codewords. Associated with each codeword, y_i, is a nearest neighbor region defined by:

$$V_i = \{x \in \Re^k : \| x - y_i \| \leq \| x - y_j \|, \quad for \quad all \quad j \neq i\} \tag{4.2}$$

The set of these regions span the entire space $\Re^k$ such that:

$$\bigcup_{i=1}^{N} V_i = \Re^k \tag{4.3}$$

In theory, an optimal codebook that best represents input vectors can be obtained by an exhaustive search for the best possible codeword in space, and the search increases exponentially with increase of codebook size *N*. This means that it is NP-hard problem, in which an optimal solution cannot be found within reasonable time. Therefore, a popular suboptimal codebook design called Linde-Buzo-Gray (*LBG*) algorithm has been used [35]. It is similar to *k*-means algorithm and its procedures are given below:

1) Initialize codebook and the size of codebook *N*.
2) Measure the input vector around each codeword by using Euclidean distance and set the input vector to the cluster of the codeword that yields the minimum distance.
3) Compute the new set of codewords by obtaining the average of each cluster.
4) Repeat steps 2) and 3) till the changes in the codewords are smaller than a preset threshold value.

4.2.3 Gaussian Mixture Model

For text-independent speaker recognition, where there is no prior knowledge of what speaker will say, GMMs [50] is the most successful likelihood function which has

been used so far. While, in text-dependent applications, where there is a strong prior knowledge of spoken text, HMM is served as likelihood function, because additional temporal knowledge can be incorporated by using it.

Mixture density models [49] (see equation 4.4) are linear combinations of simple component density functions. In Gaussian mixture density models, the component densities are of Gaussian form (see equation 4.5). Conditions $P(j) \geq 0, \forall j$ and $\sum_{j=1}^{M} P(j) = 1$ ensure that $p(x)$ is a proper density function.

$$p(x) = \sum_{j=1}^{M} P(j)\, p(x \mid j) \tag{4.4}$$

$$p(x \mid j) = (2\pi)^{-d/2} \mid \sum_{j} \mid^{-1/2} \exp^{-\frac{1}{2}(x-\mu_j)^T \sum_j^{-1} (x-\mu_j)} \tag{4.5}$$

where d is the dimension of input space, M is the number of kernels; μ_j and Σ_j are the mean and covariance of the kernel j, respectively.

GMM can be treated as a simple Bayesian network [43] with a discrete parent with j states and with M continuous children. And Gaussian mixture densities hold a universal approximation property. But the question of the model is how to estimate the model parameters $\theta = (\mu_j, \sum_j, k_j), j = 1,...,n$ from data. One can apply the principle of maximum likelihood (4.6), which can be estimated by EM algorithm.

$$l(\theta) = \log[\prod_{k=1}^{m} p(x^k \mid \theta)] = \sum_{k=1}^{m} \log \sum_{i=1}^{n} k_i N(x^k \mid \mu_i, \Sigma_i) \tag{4.6}$$

EM is a general approach to iterative computation of maximum likelihood estimates when the observations can be viewed as incomplete data [10], which implies the existence of two sample spaces Y and X and a many-one mapping from X to Y. In

Gaussian mixture models, the sample space X corresponds to the choice of a kernel having generated a data point from the sample space Y. The estimation can be divided into two steps: one is E-step, which can estimate the posterior probabilities that kernel *i* generated a data point by equation (4.7); another is M-step, which can obtain new parameter values for the mixture coefficients k and the means of the kernels, μ_j , as well as the covariances of the kernels, Σ_j , by the following equations (4.8, 4.9 and 4.10):

$$h_i^k = \frac{k_i N(x^k \mid \mu_i, \Sigma_i)}{\sum_{j=1}^{n} k_j N(x^k \mid \mu_j, \Sigma_j)} \tag{4.7}$$

$$k_i^{'} = \frac{1}{m}\sum_{k=1}^{m} h_i^k \tag{4.8}$$

$$\mu_i^{'} = \frac{\sum_{k=1}^{m} h_i^k x^k}{\sum_{l=1}^{m} h_i^l} \tag{4.9}$$

$$\sigma_i^{'} = \frac{\sum_{k=1}^{m} h_i^k (x^k - \mu_i^{'})(x^k - \mu_i^{'})^t}{\sum_{l=1}^{m} h_i^l} \tag{4.10}$$

E-step and M-steps are iterated till convergence. The EM algorithm iteratively refines GMM parameters to monotonically increase the likelihood of the estimated model for the observed feature vectors. Generally, 5~10 iterations are sufficient for parameter convergence. The EM algorithms can be found in the literature [10].

4.3 Experiment

In this section, we will verify the implementation of MFCC feature extractor and Gaussian Mixture Models (GMM) classifier for speaker recognition.The database is setup as follow: a training set includes text-independent speeches obtained from public speeches of various topics in noisy backgrounds; and a testing set with 40 voices of the

same subjects also addressing different topics. The lengths of audio data for training and testing in this experiment are 25 and 12.5 seconds per segment, respectively. To take the temporal variation of speeches into the consideration, the time interval between training and testing recordings is at least two weeks.

In experiment, we study the effect of the number of Gaussian mixture models on recognition performance while using MFCCs. The results in the table below indicated that two Gaussian mixture models could get better results to this database. Further increase the amounts of Gaussian models degraded the recognition performance, which means over fitting happens in this case [49]. Over fitting is defined that the classifier is too tuned to the training data and obtains a poor generalization on the test data.

Number of Gaussians	1	2	4	5	6	8
Error Rate	50%	47.5%	52.5%	52.5%	50%	52.5%

Table 4.1 Effect of various numbers of Gaussian models

4.4 Summary

This chapter reviewed one of popular feature extraction method, MFCCs, for speaker recognition. For readability of the dissertation, vector quantization was also briefly described in this chapter. In addition, GMM method was applied for classification. The experiment test indicated the number of Gaussian models affected recognition result. Moreover, the test result is not good to this database because of the heavy noise background when recording those speeches. For a better test result, those speeches might be denoised before feature extraction.

5 BIOMETRICS FUSION

5.1 Introduction

Given the requirement for determining people's identity, the obvious question is which technology is the best one to be suited to complete such kind of jobs. There are many different identification technologies available currently, many of which have been in widespread commercial use for many years. As discussing in Chapter 1, we know that the most common person verification and identification methods today are Password/PIN (Personal Identification Number) systems, and Token systems (such as your driver's license). Because those systems have trouble with forgery and theft problems as well as lapses in users' memory, it has developed considerable interest in biometric identification systems, which use pattern recognition techniques to identify people by employing their physiological or behavioral characteristics.

Many modalities, such as fingerprint, iris, retina, voice, face, and signature, have been used as biometric sources in biometric identification systems. Although single modal based biometric recognition has been shown to be very effective and robust under certain conditions, system performance easily degrades in the presence of a mismatch between the training and testing environment. To deal with the limitations of single modal systems, various multiple modal person recognition systems, which use more than one modality at a time, have been introduced in the literature in chapter 2.

By using multiple biometric traits, systems gain more immunity to intruder attack. For example, in audio-visual (AV) systems, it is more difficult for an impostor to impersonate another person using both audio and visual information. Meanwhile, multiple cues also improve the reliability of systems because once the performance of one biometrics is degraded for some reasons; other biometrics might not be affected by the same reasons. The advantages of applying multimode biometrics have been talked about in the previous chapters. In this chapter, we only present some conceptions for biometric information fusions in different levels.

Technically speaking, how to effectively combine biometric information from different sources is a most important issue to multimode biometric systems, because it will concern and affect the final performance results of recognition systems. Typically, biometric information fusion can occur at four major levels, namely, sensor level, feature level, score level, and decision level. Among them, integrating information at feature level is more effective than at other fusion levels, and should provide better recognition results. The reason is that the features extracted from different signals can achieve and present much more and richer information than those in other levels [51, 52].

In order to easily understand chapters 6~10, section 5.2 presents the basis of information fusion; and summary is presented in section 5.3.

5.2 Information Fusion

A typical single biometric process includes these steps (see Fig. 5.1):

- Biometric capture: for example, iris scanner, voice recorder, fingerprint reader, camera for photos;

- Feature extraction: it is a software to select the active matching data and produce feature vectors in feature space;
- Matching: it is used to compare the captured biometrics with an existing database which come from enrollment;
- Decision: it is a final classification result to provide a confidence in any identity matched against the subject under test.

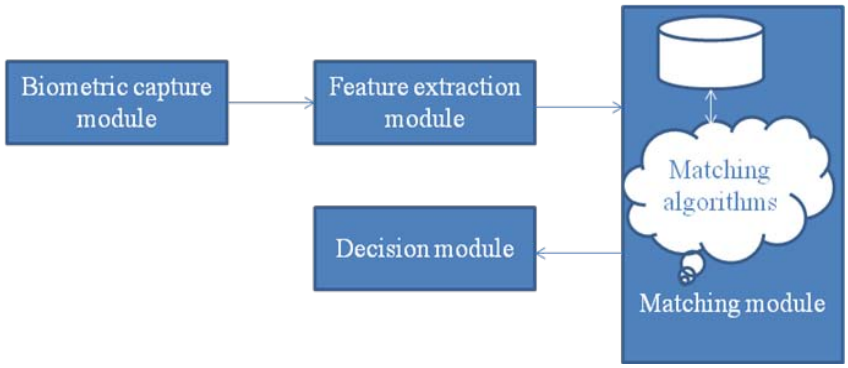


Figure 5.1 Process of single modal biometrics

Multiple modal biometrics fusion can happen at different modules in the above figure; the commonly used fusion options are: score and decision levels. At both levels, each biometric process makes its own recognition scores or decisions, and then the fusion process fuses them together with combination algorithms to make final decision. The following gives the basic idea about the four possible fusion strategies:

- Sensor Fusion Level: It is an information processing technique through which information produced by several sources can be combined optimally. The human brain is a good example of a complex, multiple sensor fusion system because it can receive five different signals (smell, touch, taste, hearing, and sight) from five different sensors (nose, skin, tongue, ear and eyes) and fuses

those signals to make a decision or judgment or control. Research about sensor fusion has been traced back to the early 1980s [11].

- Feature Level Fusion: The data captured from each sensor is used to create feature vectors. And those feature vectors can be homogeneous or non-homogeneous. The fusion processes fuse the collection features into one feature set and send the fused set to matching and decision module to make final decision. Combining feature vectors from each biometrics creates a vector that has a higher dimensionality and higher probability of uniquely identifying a person in feature space. In feature level fusion, biometric information are combined either by concatenation or by applying a weighted summation [51] before being presented to a pattern classifier (see Fig. 5.2). When feature vectors are homogeneous (e.g., feature vectors of multiple fingerprint impressions), a single resultant feature vector can be calculated as a weighted average of the individual feature vectors. When feature vectors are non-homogeneous (e.g., feature vectors of different biometric modalities like face and voice), we can concatenate them to form a single feature vector.

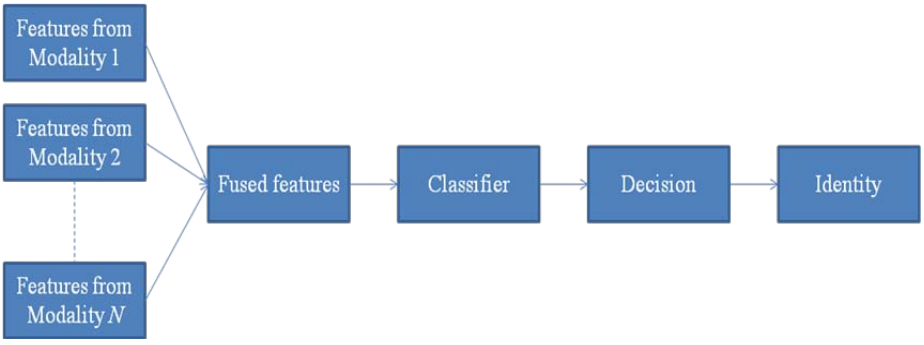


Figure 5.2 Feature fusion

- Matching Score Level Fusion: Integration of information at matching score level is the most common approach in multimodal biometric systems. And it is also known as fusion at the *measurement level* or *confidence level* [51]. Once the feature vectors from each biometric modal have been extracted, they are passed to their individual matching algorithms, which attempt to match them against previously captured templates. When biometric matchers output a set of possible matches along with the quality of each match (matching score), the individual matching scores are then combined (a variety of methods may be used, e.g., Neural Networks, or Weighted Sums) to form a result from which a decision may be made (see Fig. 5.3). But before such combination of matching scores, scores must be transformed to a common domain first to ensure the meaningful combination of scores [9, 51]. Next to feature vectors extraction, matching score output by the matchers contain the richest information about input pattern. Meanwhile, it is relatively easy to access and combine the scores generated by different matchers. The fusion can be done by weighted summation rule, weighted production rule, Max rule and Min rule. The functions of weighted summation method and production method are given as follows [33]:

$$s = \sum_{i=1}^{K} w_i s_i \tag{5.1}$$

$$s = \prod_{i=1}^{K} (s_i)^{w_i} \tag{5.2}$$

where K is the modality number, w_i the ith fusion weight, and s_i the ith score obtained from the ith modality. A basic assumption of (5.2) is that scores from different modalities are statistically independent; however this assumption is unrealistic in many situations.

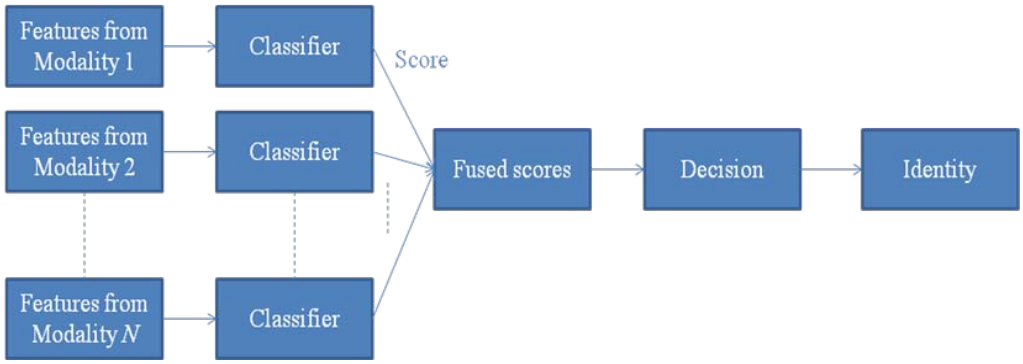


Figure 5.3 Matching score fusion

- Decision Level Fusion: Strictly speaking, decision level fusion is not a 'truly' fusion, although it is generally termed as such. The principle behind this method is that each biometric system makes a match based solely upon the biometrics it captures and then passes a binary "match/no-match" vector to a decision module [56], which forms a conclusion based on a majority vote scheme, AND, and OR operators. In majority voting, final decision is based on the number of votes made by individual classifiers. However, it cannot be done when there is an even number of sensors with the decisions made by half of classifiers does not agree with the other half. AND rule is very strict and therefore suitable only for systems that require low false acceptance; unlike

AND rule, the OR rule can make a decision as soon as one of the classifiers make a decision. It is suitable for the systems that can tolerate a loose security policy. Some systems also include a method to weight the decision towards more highly regarded biometrics (e.g., iris over retina scans).

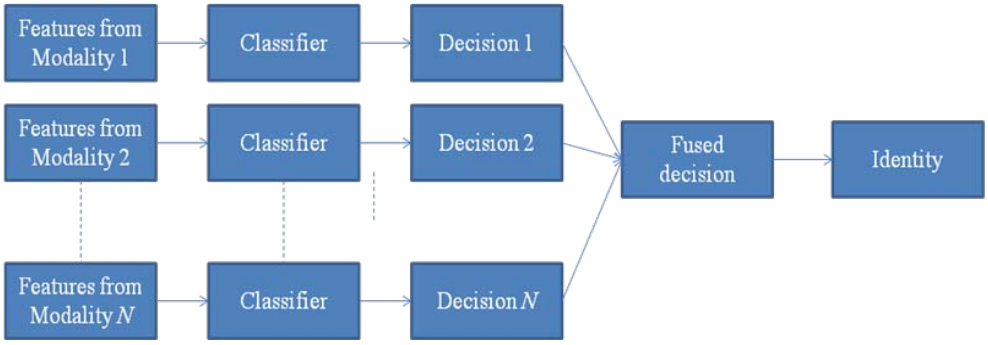


Figure 5.4 Decision fusion

Most observers accept that fusion produces better results when performed at feature extraction level rather than at the data matching or decision levels, because the data is combined at its most information rich stage and before external contamination from matching algorithms. However, feature level fusion is difficult, as the relationship between individual biometrics' features spaces may not be straightforward [53]. The problems associated with feature level fusion are noted in the literature [26], with most fusion research being carried out in the data matching and decision level fusion areas.

5.3 Summary

Information fusion is a key issue in a multimodal biometric system, and it can possibly take place in four levels, that is, sensor, feature extraction, matching score and decision levels. Sensor level fusion is seldom used in commercial applications because of compatibility problems. In other words, fusion at this level requires that the information obtained from different multiple biometric sensors must be compatible, and that will be a

rare case with biometric sensors. Also, fusion at feature level is not always guaranteed feasible, because the feature sets extracted from different biometric modalities may either be inaccessible or incompatible to each other. Combination at matching score level is easy to use in some degrees, and it has been researched and developed a lot since the beginning of multimode biometric systems; meanwhile, it is easy to be used. The main problem at this fusion level is to obtain the score weights of different modalities. Fusion at decision level cannot represent the whole pictures of multimodal system, because only a limited amount of information is available for fusion. Although multiple modal systems can deal with the limitations of single modal systems and gain a lot of benefits, it should be used with caution because catastrophic fusion may occur if biometrics is not properly combined; such situations might happen if the results of fused strategies are worse than those of any single modal revolved in the fused systems.

6 FUSION BY SYNCHRONIZATION OF FEATURE STREAMS

6.1 Introduction

Multiple modal biometrics systems, which use more than one biometrics modality like retinas, irises, hand geometries, fingerprints, handwriting, audio and faces, have been introduced in literature in chapter 2 to overcome the shortcomings of single modal biometrics. And biometrics fusion, which integrates information from the applied modalities and is implemented at several levels such as sensor fusion level, feature fusion level, score fusion level, and decision fusion level, has becoming a critical issue in multiple modal biometric systems.

Among the candidate modalities, both audio and face (visual) recognitions are considered to be easy to use, and the low cost of audio and visual sensors also make it feasible to deploy such audio-visual (AV) systems for surveillance, security, digital libraries, forensic work, law enforcement, human computer intelligent interaction, and smart environments etc. Moreover, in an AV system, the audio-based authentication part can be classified into two categories: *text-dependent* and *text-independent* [3]. In a text-dependent AV system, speakers must recite a phrase, password or numbers specified by the system. This is in contrast to a text-independent system, where speakers can say whatever they wish to say. That will give more freedom to the system and people. Therefore, one of the principal advantages of a text-independent AV system is that it allows the system to be applied to much more diversified tasks. For those reasons, this

chapter applies the proposed intuitive feature fusion methodology for multi-mode biometric person recognition systems, especially concentrates on Audio-Visual based Text-Independent (AVTI) system to test it in this chapter. Also, in the future chapters, AVTI system is used as testing examples for other proposed optimized algorithms.

As stated before, in biometrics fusion, integrating information at an early stage, like feature stage, is more effective than at later stages. Many works for multi-mode biometric systems have been done so far. And some representative researches and studies have been presented in Chapter 2 in details. But, the methods discussed in the literature in Chapter 2 include using lip movement or partial face images to represent visual cue in AV systems, and almost all of them except Luettin [37] integrated multiple modal results in score or decision fusion level. In Luettin's work, lip movement from video streams and text-dependent speeches were examined in the feature fusion level by concatenation with the frame rate of the speeches.

This chapter introduces a novel person recognition approach. The testimony has been done by using still face images and text-independent speech signals. In the proposed method, the reason why the above two modalities are much more favorable to be used than other modalities by the authors is that 1) still face images instead of video information are considered to reduce storage space and computational complexity, and 2) text-independent speech signals are used to allow AV systems more flexible for diversified applications. Furthermore, both biometrics will be integrated at feature fusion level by a novel synchronization method and exported to a PNN framework. A perfect recognition rate has been achieved by applying the new feature fusion strategy to a virtual database composed of 40 subjects.

The remaining of the chapter is organized as follows: Section 6.2 briefly reviews feature extraction of AVTI system; Section 6.3 introduces the intuitive synchronization method at feature level fusion; Section 6.4 examines this method; and the conclusion is presented in Section 6.5.

6.2 Feature Extraction of AVTI system

As mention above, AVTI system in this chapter is different from other AV systems in literature. The proposed methodology in AVTI system includes feature extractions from visual images using the Pyramidal Gabor - Eigenface (PGE) algorithm [20] and from audio signals using the Mel Frequency Cepstrum Coefficients (MFCCs) and Vector Quantization (VQ) algorithms. The extracted features from both modalities are normalized and fused to recognize the subjects under a PNN framework. Due to different sampling rates used in the system, the extracted PGE features from still images should be synchronized to fit the compressed audio features. For the continuity of this chapter and the convenience of readers, the following will describe face and voice recognition in brief respectively. For detail information, readers can go back to Chapter 3 & 4.

6.2.1 Audio feature extraction

One of popular methods for audio feature extraction is to apply MFCCs algorithm. Such method is very straightforward. Several processing steps occur to obtain the audio fe**a**tures in this chapter (see Fig. 6.1).

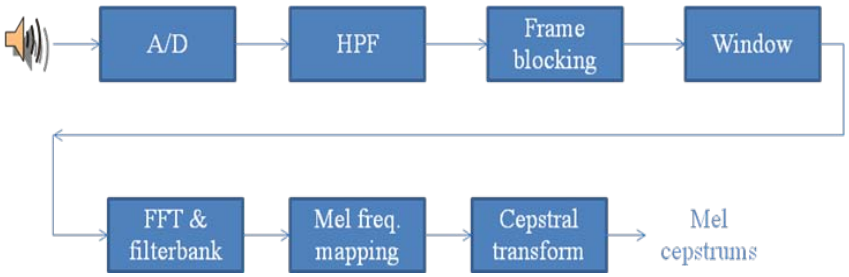


Figure 6.1 Procedures of MFCC

In Fig. 6.1, high-pass filter is used to enhance those high frequencies in signals that are generally attenuated during recording process. After the procedures of Hamming windowing, short-term speech segments with a length 20ms and an overlap of 10ms per frame [3] are processed by Fast Fourier Transform and Mel-filter banks to get the Mel spectrums. Then, discrete cosine transform (DCT) is applied to log of the filtered frequency components to obtain Mel cepstrum. Considering the amount of feature sets for each subject, Mel cepstrum has to be compressed by a VQ algorithm before being fused in the proposed method.

6.2.2 Visual feature extraction

The visual features are extracted by the PGE algorithm [18, 20]. Such algorithm is effective for person recognition because:

1) It utilizes 1-D filter masks instead of 2-D filter operation in spatial domain to obtain Gabor features, which make it faster and more flexible with less computational complexity than the classic Gabor-based recognition method that needs to perform 2-D Fourier transform and inverse Fourier transform;
2) The Eigenface method further reduces the redundancy of Gabor features.

PGE algorithm consists of training and recognition stages. During training stage, the features of training sets are obtained by applying the pyramidal Gabor wavelet procedure [44] to training sets in four levels and four orientations (see 6.1 and 6.2). To encompass the features of each training face image, the rows of all its feature representations will derive an augmented feature representation *via* concatenation. Then,

the augmented feature representations for all training images are normalized to zero mean and unit variance. Later, the Eigenface method [55] transforms them into the eigenspace.

The second stage of PGE algorithm uses equation (6.2) to extract the visual features of testing face images, and projects the test difference vectors into eigenspace.

In the above procedure, Gabor function (6.1) of frequency f_0, orientation θ_0, and centered at ($x_0 = 0$, $y_0 = 0$) is defined as a sum of two separable filters (see equation (6.2)) [20]:

$$g_{0,0,f_0,\theta_0}(x,y) = \exp(-\pi a^2(x^2+y^2)) \cdot \exp(j2\pi f_0(x\cdot\cos\theta_0 + y\cdot\sin\theta_0)) \tag{6.1}$$

$$\begin{aligned} R_{0,0,f_0,\theta_0,p=0}(x,y) &= [g_x\cdot\cos(2\pi f_0 x\cos\theta_0)]\cdot[g_y\cdot\cos(2\pi f_0 y\sin\theta_0)] \\ &\quad -[g_x\cdot\sin(2\pi f_0 x\cos\theta_0)]\cdot[g_y\cdot\sin(2\pi f_0 y\sin\theta_0)] \end{aligned}$$

$$\begin{aligned} R_{0,0,f_0,\theta_0,p=1}(x,y) &= [g_x\cdot\sin(2\pi f_0 x\cos\theta_0)]\cdot[g_y\cdot\cos(2\pi f_0 y\sin\theta_0)] \\ &\quad -[g_x\cdot\cos(2\pi f_0 x\cos\theta_0)]\cdot[g_y\cdot\sin(2\pi f_0 y\sin\theta_0)] \end{aligned} \tag{6.2}$$

where g_x and g_y are 1-D Gaussian function $g_x = \exp(-\pi a x^2)$ and $a = (3\sqrt{\ln 2/\pi})^{-1} f_0$. Each block in (6.2) is a 1-D filtering operation. By performing a constrained least squares minimization of the error of frequency response [44], four 1-D Gabor masks can be obtained. If θ_0 is 0^0, 45^0, 90^0, 135^0, respectively, these filters can be used to get the robust Gabor features in four orientations and four levels.

6.3 Feature fusion

Biometric fusion is the critical part in any multi-modal biometrics system and there are several level fusions. Among those levels, fusing information at feature stage is more effective than at later stages. So far, some work about different AV systems has been done to recognize persons *via* score or decision fusion. In this chapter, both biometrics in

AVTI system will be integrated at feature level by a novel synchronization method. Before fusing the features extracted from different modalities, one should normalize them to overcome the problems caused by different feature spaces, the variations in their ranges and distributions of the individual feature vector values.

Meanwhile, synchronization is also important to an AV system. As an example, given 128 compressed audio feature vectors and 6 PGE visual feature vectors for each subject, every *int*(128/6) voice feature vectors will be concatenated with one identical face feature vector: that is, duplicated visual feature frames are inserted to audio feature vectors. Therefore, the compressed feature sets extracted from audio and visual signals are synchronized by the way shown in Fig. 6.2, and then concatenated to obtain the new augmented feature representations which are exported to the PNN framework.

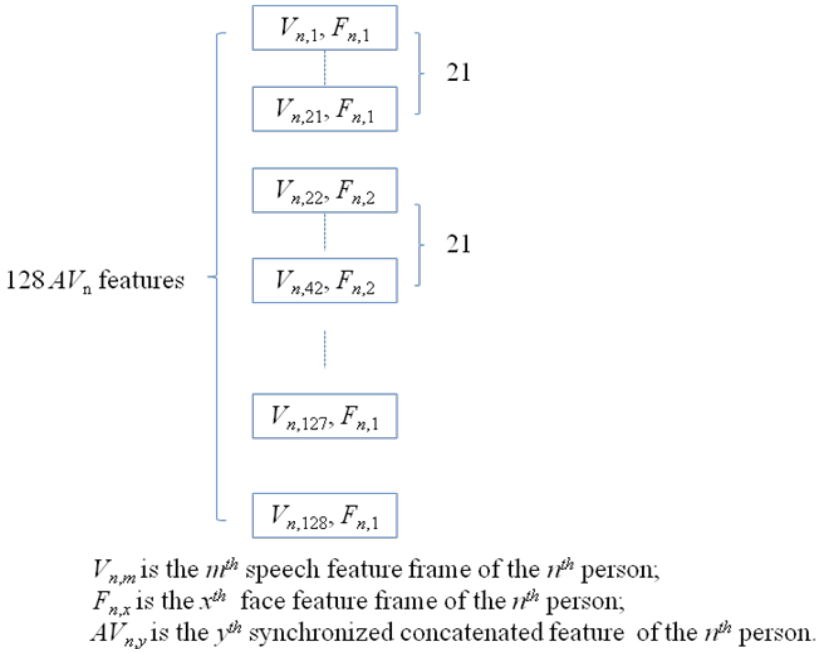


Figure 6.2 Example of synchronization

PNN is a type of feed-forward neural networks with four layers: input layer, two hidden layers, and output layer. It applies a standard Bayesian classifier and maps any

input pattern into a number of classifications without training because the conventional training vectors simply become the weight vectors in the first hidden layer [48]. It inherits the parallel structure that can be easily extended by adding new training samples or removing the existed training samples. The activation function of a neuron in the PNN framework of AVTI system is statistically derived from an estimation of probability density functions (*pdf*) based on the training data sets, and it can approximate the *pdf* of the training subjects. The *pdf* of a given input pattern $\boldsymbol{z}$ belonging to one subject can be estimated by

$$g_k(z) = \frac{1}{\sigma} w(\frac{z - b_k}{\sigma}) \tag{6.3}$$

where $\boldsymbol{z}$ is the given input pattern, $\boldsymbol{b}_k$ the k^{th} pattern of subject C, w the evaluation function, and σ the smoothing parameter.

The average value of *pdf*'s for the "*M*" patterns of subject C can be used as the estimate of *pdf* for this subject:

$$h(z) = \frac{1}{n\sigma} \sum_{k=1}^{M} g_k(z) \tag{6.4}$$

When Gaussian functions are used as the evaluation functions, the *pdf* of a given input pattern $\boldsymbol{z}$ belonging to the k^{th} pattern of one subject can be estimated by equation (6.5), and the estimation of the *pdf* for a feature vector $\boldsymbol{z}$ belonging to subject C_i is given by equation (6.6):

$$g_{k,i}(z) = \frac{1}{(2\pi)^{p/2} \sigma^p} e^{\frac{-\|z - b_{k,i}\|^2}{2\sigma^2}} \tag{6.5}$$

$$h_i(z) = \sum_{k=1}^{M} g_{k,i}(z) \tag{6.6}$$

where $k = 1, 2, \ldots, M$, $i = 1, 2, \ldots N$, M the number of the feature vectors of subject C_i; N the number of subject classes, p the length of $\boldsymbol{z}$, σ the smoothing parameter, $\boldsymbol{b}_{k,i}$ the k^{th} pattern of subject C_i.

Fig. 6.3 & 6.4 show the related architectures of PNN and AVTI system with feature fusion. In Fig. 6.4, N denotes the number of persons in training data set; X is set as the input of the PNN for a subject to be classified; AV_i is the i^{th} feature vector of X. The AV patterns for each subject, resulted from the training stage, are used as the weights of its first hidden layer. The outputs of each node of the first hidden layer are obtained using (6.5). The summation layer adds all the estimates of the *pdf* for the feature vector X belonging to subject C_i ($i = 1, 2, \ldots, N$) with (6.6). The competitive network applies the rule of "winner-take-all" to classify the input X using the following equation:

$$I = IND\{MAX(h_1, h_2, ..., h_N)\} \tag{6.7}$$

where h_i is from equation (6.6), *MAX*() and *IND*() denote max and index operations, respectively.

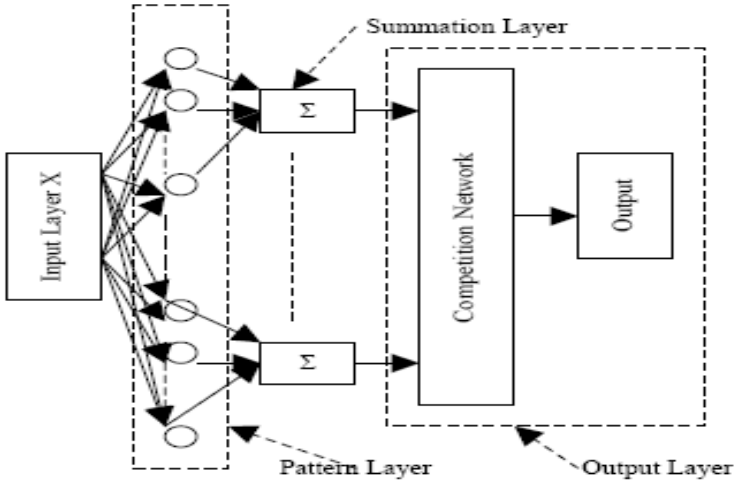


Figure 6.3 PNN architecture

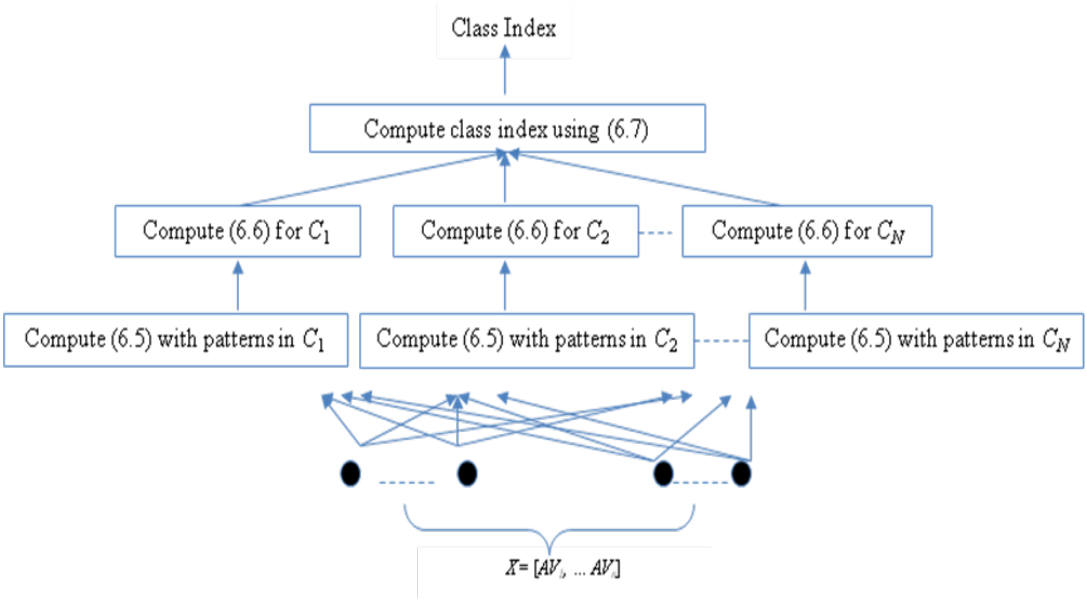


Figure 6.4 PNN structure for AVTI system.

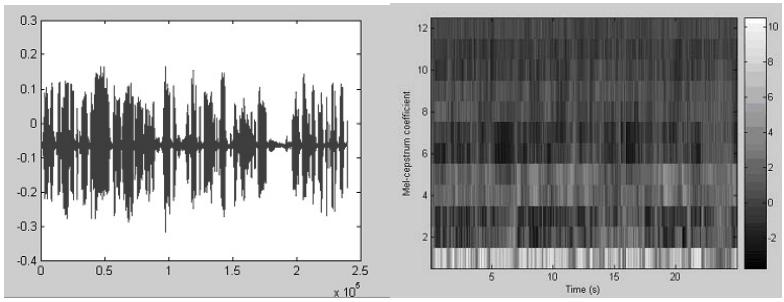
6.4 Experiments

6.4.1 Experimental setup

A database including 40 subjects was constructed to test the proposed method. It consisted of audio and visual parts. In audio part, a training set included text-independent voices obtained by the same microphone from the public speeches of various topics in noisy backgrounds; and a testing set with 40 voices of the same subjects also addressing different topics. The lengths of audio segments for training and testing were 30 and 15 seconds, respectively. To take the temporal variation of speeches into the consideration, the time interval between training and testing recordings was at least two weeks.

The visual part of the database was from AT&T database. There were totally 40 subjects and each subject had 10 images taken with different poses and expressions. Six out of the 10 images of each subject were randomly picked to construct the training set, and the rest the testing set. Finally, a virtual subject was constructed by assigning an audio subject to a visual subject, which created a large number of virtual subjects.

Fig. 6.5(a) shows a sample of audio signal. And the 30-second audio was sampled at 8 kHz. Fig. 6.5(b) presents its 12 Mel-filter bank cepstrum coefficients.



(a) (b)

Figure 6.5 (a) Audio sample; (b) 12 Mel cepstrum coefficients.

Fig. 6.6(a) shows one of the visual samples in the AVTI virtual database, and Fig. 6.6(b) displays the magnitude of the features extracted by PGE algorithm.

(a) (b)

Figure 6.6 (a) a visual sample; (b) PGE Features.

6.4.2 Results for the proposed method

In order to compare the performances from the proposed method and from the two related single modal methods under the PNN framework, two experiments were conducted. In experiment 1, it was chosen that, for each virtual subject, the length of the audio signals was 25 seconds for training and 12.5 seconds for testing; and in experiment 2, 20 seconds for training and 10 seconds for testing. In both of the experiments, six face images of each subject were employed for training and four remaining face images for testing. In addition, the codebook size for VQ was initialized as 128. Furthermore, the number of MFCC coefficients was set to 12.

Table 6.1 compares the results from the proposed AVTI recognition method and from the two related single modal methods in the PNN framework. With the setup described above, the proposed AVTI recognition system obtained the perfect recognition rate of 100%. However, if only the audio-based features were used for human identification, implemented with a similar PNN structure, the recognition rates were only 47.5% and 43.5%, respectively; and the recognition rate was improved to 96% by using only the visual-based features. Such results suggest that the proposed method is clearly worthy of further study.

Methods	Recognition rate for best performance length of training audio (s) / length of testing audio (s)	
	25s / 12.5s	20s / 10s
Audio-based modal	47.5%	43.5%
Visual-based modal	96%	96%
Proposed method	100%	100%

Table 6.1 Comparison for various methods

The proposed method was also compared with the Minimum Distance (MD) classification method, which was very simple and classified an object under a minimum distance criterion of the fused features. The results in Table 6.2 indicate that AVTI system under the framework of PNN performed much better than the MD method, because MD method does not utilize statistical information for the fused features.

Methods	Recognition rate for the best performance (Length of training time (s) / length of testing time(s))	
	25s / 12.5s	20s / 10s
Proposed method	100%	100%
MD method	85%	87.5%

Table 6.2 Comparisons of the proposed method and MD method

Shown in Table 6.3 are the recognition rates *vs.* the lengths of AV feature vector.

Length of AV feature	Recognition rate	
	25s / 12.5s	20s / 10s
22	90.0%	87.5%
24	90.0%	92.5%
26	92.5%	95.0%
28	97.5%	97.5%
31	100%	97.5%
32	97.5%	100%

Table 6.3 Recognition rate vs. length of AV feature vector

The AV feature vector consisted of 12 MFCCs for the audio part and the first several maximum PGE eigenvectors for the visual part. Table 6.3 shows that the perfect recognition rate is achieved with the length of the feature vector being less than or equal to 32. Among the 32 components, 12 were MFCCs, therefore, only at most 20 PGE eigenvectors were needed to obtain the much better recognition rate in the AVTI person recognition system. It demonstrates the proposed method has overcome the problem of different frame rates from audio and visual signals and the curse of dimensionality in the feature fusion procedure in some degrees.

6.5 Conclusion

A method for integrating audio and visual biometrics at feature level has been presented in this chapter. The described framework can synchronize the compressed visual and audio features to form a mixed feature space efficiently. It has been shown through experimental studies that the integrated method to the AVTI system at fusion of feature level can achieve superior performance in comparison to any of the individual biometrics it derives. In addition, since only still images are needed for the implementation of the approach, the storage space and process time can be more economical compared to techniques based on integrating video with audio information. The testing results of the AV system also indicate that the proposed algorithm overcomes the problem of different frame rates from the audio and visual signals and the curse of dimensionality normally existed in a feature fusion procedure.

7 FUSION BY LINK MATRIX ALGORITHM AT FEATURE LEVEL

7.1 Introduction

Biometric identification and authentication systems can be classified as single modal systems and multiple modal systems. As stated before, although single modal system has been shown to be effective and robust under certain conditions, system performance degrades in the presence of sensory noise and mismatch between training and testing environments. In order to overcome its shortcomings, various multiple modal systems, which use more than one modality at a time, have been addressed in the literature in chapter 2. Moreover, choice of biometric modalities depends on factors such as accuracy, robustness, sensor size and cost.

The goal of this chapter is to devise an effective method to integrate biometric information from multiple modals, as an example, audio and visual (AV) biometric modalities have been applied to implement and test the proposed methodology at feature level. Of course, depending on different types of audio and visual signals used, AV systems can be any of the followings: visual-static text-dependent speech, visual-static text-independent speech, visual-dynamic text-dependent speech, and visual-dynamic text-independent speech systems. In this chapter, visual-static text-independent speech bi-modal system is employed as the specific AV system.

There exist many fusion methods in the studies of multiple modal biometrics; methods for AV systems listed in Chapter 2 have been almost exclusively focused on

using either lip movement or video to represent visual cues and integrate multiple cues by score fusion and/or decision fusion. Investigators have seldom studied biometric fusion at feature level because there are some difficult issues, especially for AV feature fusion. But, there appears to be a consensus [20, 33] that integrating information at feature level is more effective than doing so at higher levels. Therefore, feature level fusion should be taken a shot. However, before fusing features from audio and visual signals, audio and visual feature streams have to be synchronized, and this may lead to a high dimensionality, that is a very bad news to the fusion algorithms. In order to fuse the information from multiple modalities effectively, this chapter apply the proposed method to combine feature vectors (see Fig. 7.1). Cost function, constraints and possible simplifications are outlined. A heuristic algorithm which is suitable for biometric applications is proposed. Once audio and visual features are combined to form an integrated feature vector, they are fed to a block similar to Radial Basis Functions (RBF) [7] to perform classification. Experiments are carried out for 40 subjects from a virtual database consisting of face images and speech clips. The results show that 1) the proposed method performs better than those without fusion, and 2) it is more reasonable than the one in Chapter 6.

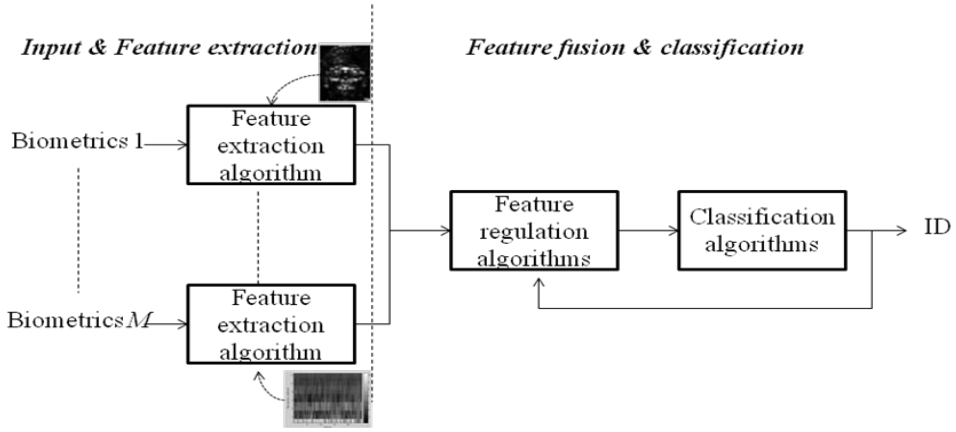


Figure 7.1 Procedures of the proposed feature fusion method

The remainder of this chapter is organized as follows: Section 7.2 provides some preliminaries and Section 7.3 proposes a fusion method for integrating features from two biometric sources. In Section 7.4, a classification method is proposed which is similar to RBF that analyzes the probability density functions (*pdf*s) of the feature vectors. Some results from experimental studies are presented and discussed in Section 7.5 and the chapter ends with concluding remarks in Section 7.6.

7.2 Preliminaries

In any person recognition system, feature extraction of individual modality is one of the most essential steps, because the performance of systems strongly relies on the accurate extraction of biometric features. When considering audio feature extraction for speaker recognition, in theory, it should be possible to recognize speakers directly from waveforms. Because of the large variability of speech signals, it is, however, a good idea to extract essential features from speech signals. This is also true for face recognition. Thus, feature level fusion is an attractive approach, which is the main reason that we focus on feature based biometric fusion. Some basic concepts and algorithms are briefly stated here for completeness.

In the AV system under investigation, visual and audio features are extracted by pyramidal Gabor wavelet with eigenface (PGE) algorithm [20] and Mel Frequency Cepstrum Coefficients (MFCCs) algorithm [3], respectively.

In PGE algorithm, involvement of Gabor wavelets benefits face recognition and makes it more robust against variations from lighting condition and viewing direction. In addition, to save computational cost and memory space, a pyramidal structure is used in

spatial domain to avoid the procedures of Fourier transform and inversed Fourier transform, which are often utilized in general 2-D Gabor based face recognition methods.

The central task of a typical audio-based feature extraction procedure is to parameterize speech signals into a sequence of feature vectors that are less redundant for statistical modeling. Spectral features, such as Linear Predictive Cepstrum Coefficients (LPCCs) or Mel Frequency Cepstrum Coefficients (MFCCs) have been widely used [3]. In this section, the procedure of MFCCs is also outlined. The above feature extraction methods have been discussed in Chapter 4 and 5 in details. For the relevant information, please go back and read those chapters.

7.3 A method to fuse features

In this section, biometric information fusion is formulated as an optimization problem. Cost function, constraints and solution strategies are discussed with a simple example. The method developed is then applied to fuse audio and visual feature vectors.

Given feature vectors from two sources, the task is to combine them so as to optimize certain performance criteria, such as computational cost and accuracy. We use a simple example to illustrate the essence of the proposed method. Suppose that two modalities, M_1 and M_2, are used in individual biometric algorithms. Suppose also that the i^{th} subject S_i in modality M_1 and M_2 has 3 and 5 components, respectively, a component $\{a_{1i}, a_{2i}, a_{3i}\}$ belongs to the i^{th} subject S_i in modality M_1, and components $\{v_{1i}, v_{2i}, v_{3i}, v_{4i}, v_{5i}\}$ belong to S_i in modality M_2. We can then define a 5x3 *Link Matrix B*, whose entries are either 1 or 0, with 1 denoting a pair of variables (or vectors) selected to form a new vector from an individual modality. For instance, if $b_{12} = 1$, where b_{ij} is the ij^{th} entry of B, then v_{1i} and a_{2i} are selected to be part of a feature vector in the form of $[v_{1i}\ a_{2i}]^T$.

To further illustrate the idea, let us use equation (7.1) as an example. The first row of the B matrix [1 0 0] in (7.1) means that the first feature component v_{1i} of subject S_i in modality M_2 joins the first feature vector a_{1i} of subject S_i in modality M_1. The second row of the B matrix [0 1 0] implies that the second feature vector v_{2i} of subject S_i in modality M_2 joins the second feature vector a_{2i} of subject S_i in modality M_1. Going through all the rows, the matrix B given in (7.1) implies that an *Integrated Feature Vector* $\boldsymbol{q}_i = [v_{1i}\ a_{1i}\ v_{2i}\ a_{2i}\ v_{3i}\ a_{1i}\ v_{4i}\ a_{3i}\ v_{5i}\ a_{2i}]^T$ is obtained, given individual biometric vectors $[v_{1i}\ v_{2i}\ v_3\ v_{4i}\ v_{5i}]^T$ and $[a_1\ a_{2i}\ a_{3i}]^T$. This *Integrated Feature Vector* will then be fed to a classification algorithm for further biometric authentication/identification.

$$B = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \tag{7.1}$$

Graphically, the relationship specified by (7.1) can be illustrated by the diagram shown in Fig. 2.

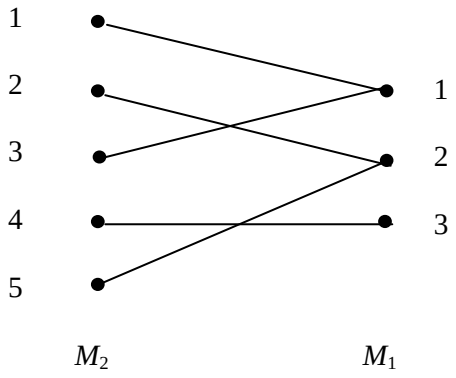


Figure 7.2 Illustration of Link Matrix B between modality M_1 and M_2.

With the *Link Matrix B* defined, we can formulate the problem of combining features from two biometric sources in terms of Link Matrix selection. Let us generalize the notation used in the previous example as follows:

- a_{ij}: the i^{th} component of subject S_j in modality M_1, where $i = 1,\ldots, m$; m is the number of components in M_1. Note that a_{ij} can be a vector.
- v_{kj}: the k^{th} component of subject S_j in modality M_2, where $k = 1,\ldots, n$; n is the number of components in M_2.
- b_{ik}: the entry of matrix B in i^{th} row and k^{th} column. Further, $b_{ik} \in [0,1]$, where $b_{ik} = 1$ if a_{ij} in M_1 joins v_{kj} in M_2; otherwise, $b_{ik} = 0$.

Let us now define an error function, E, against which the accuracy performance of a biometric identification/authentication algorithm is to be judged. We desire a structure for B that is as simple as possible to reduce the computational cost. These and other objectives are summarized next.

1) It is desirable that the error function be minimized; i.e.,

$$Q_1(B) = E(B), \tag{7.2}$$

2) It is also desirable that the length of the Integrated Feature Vector be minimized. This is equivalent to minimizing Q_1, where

$$0 < Q_2(B) = \frac{\sum_{i=1}^{m}\sum_{k=1}^{n} b_{ik}}{m * n} \leq 1, \tag{7.3}$$

3) Each component in modality M_1 and M_2 appears at least once in the Integrated Feature Vector; i.e.

$$\begin{aligned} Q_{3i} &= \sum_{k=1}^{n} b_{ik} \geq 1 \\ Q_{4i} &= \sum_{i=1}^{m} b_{ik} \geq 1, \end{aligned} \tag{7.4}$$

where $i = 1, \ldots, m$; $k = 1, \ldots, n$.

Taking into consideration the above factors, the optimization problem is equivalent to minimizing the following objective function by choosing the *Link Matrix B*,

$$C(B) = E(B) + \lambda Q_2(B)), \tag{7.5}$$

subject to (7.4), where $0 \le \lambda \le 1$.

Assume that $n > m$, set Q_{3i} to 1; that is

$$\begin{aligned} Q_{3i} &= \sum_{k=1}^{n} b_{ik} = 1, \\ Q_{4i} &= \sum_{i=1}^{m} b_{ik} \ge 1 \end{aligned} \tag{7.6}$$

In this case, each component of the given subject in modality M_2 is guaranteed to be picked up once and only once to form the Integrated Feature Vector. Note that whenever this occurs, Q_2 becomes a fixed number and objective function; therefore,

$$C(B) = E(B) \tag{7.7}$$

Mathematically the case in which $m > n$, $Q_{3i} \ge 1$ and $Q_{4i} = 1$ can be treated similarly to that given by (7.6) and (7.7).

The following remarks can be made about the solutions of the proposed problem:

- An exhaustive search [30] works fine with simple problems having relatively low dimensionality. Such a solution examines all possible choices of the Link Matrix *B* and the associated objective function values. This may not be a viable solution when the size of the problem becomes large.
- Blind random search [30] over the domain of interest is a method aimed at reaching an acceptable solution. The eventual solution is obtained simply by taking the choice of *B* that yields the lowest *C* value among the randomly tested candidate solutions.

- Heuristic search [30] is another method that exploring the structure of the solution space and guiding the search directions. This approach may not always find the best result, but normally efficiently finds a near-optimal solution.

A simple search procedure is proposed in this chapter to obtain a sub-optimal solution. In each iteration, a configuration of B is randomly generated. If the solution results in a better value of the objective function, it will be kept and set as the current chosen solution; otherwise, it will be ignored. The following steps are applied to obtain the Link Matrix B:

1) Randomly generate a matrix B that satisfies (7.4) (or (7.6));
2) Compute the objective function C with the matrix B using (7.5) (or (7.7));
3) Save both matrix B and result C, and set B as B_{best} and C as C_{best}, regarding B_{best} as the current solution;
4) Randomly generate another matrix B that satisfies (7.4) (or (7.6));
5) Evaluate the objective function C using (7.5) (or (7.7)) with the new matrix B obtained in Step 4:
   a) If C is better than C_{best}, replace B_{best} with the new B and update C_{best}.
   b) Otherwise, just ignore the new solution.
6) Iterate the steps 4) and 5) till either the error C is below a preset tolerance or the maximum number of iterations is reached.

7.4 Case Studies

A simple example is given here to illustrate the method proposed above. In this example, we assume that there are three subjects S_1, S_2 and S_3, and each subject has two

modalities to represent it: the shape modality M_1 and color modality M_2. In modality M_1, three patterns of each subject are assumed to be the training data set and the fourth is assigned as the testing data set. In modality M_2, six patterns of each subject are assumed to be the training data set, and another six are assigned as the testing data set. In addition, data streams consisting of 1 and 0 represent each pattern in M_1 and M_2. Fig.7.6 and Table 7.2 show the patterns of three subjects S_1, S_2 and S_3 in modality M_1 and M_2, respectively.

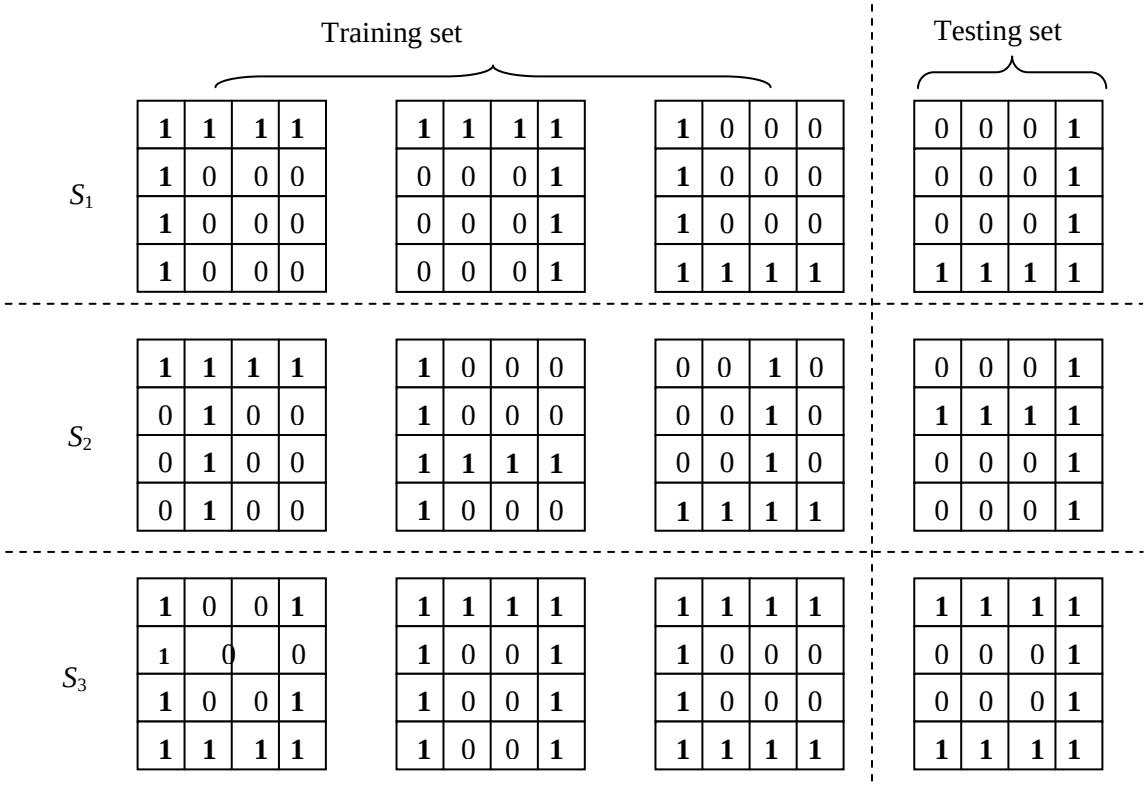


Figure 7.3 Patterns for subject S_1, S_2 and S_3 in modality M_1, respectively

Using the method given in Section III.A, a Link Matrix *B*, obtained using (7.6) and (7.7), is shown in Equation (7.8). With this Link Matrix, a perfect classification is obtained.

	Training set						Testing set					
Patterns for S_1	1	0	0	0	0	0	1	0	0	0	0	0
	0	1	0	0	0	0	0	1	0	0	0	0
	0	0	1	0	0	0	0	0	1	0	0	0
	0	0	0	1	0	0	0	0	0	0	1	0
	0	0	0	0	1	0	0	0	0	1	0	0
	0	0	0	0	0	1	0	0	0	0	0	1
Patterns for S_2	1	0	1	0	0	0	0	0	1	0	1	0
	0	1	0	1	0	0	0	1	0	1	0	0
	0	0	1	0	1	0	1	0	1	0	0	0
	0	0	0	1	0	1	0	0	0	1	0	1
	0	0	0	1	0	1	0	1	0	1	0	0
	1	0	1	0	0	0	0	0	0	1	0	0
Patterns for S_3	1	1	0	0	0	0	0	0	1	1	0	0
	0	0	1	1	0	0	0	0	0	0	1	1
	0	0	0	1	1	0	0	1	1	0	0	0
	0	0	0	0	1	1	0	0	0	1	1	0
	0	0	1	1	0	0	0	1	1	0	0	0
	0	1	1	0	0	0	0	1	0	1	0	0

Table 7.1 Patterns for subject S_1, S_2 and S_3 in modality M_2

$$B = \begin{bmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \tag{7.8}$$

7.5 Proposed Classification Method

After features from both audio and visual signals are integrated, another factor affecting system accuracy is the choice of classification method. Classification attempts to assign a measurement to a class or identify the source of a measurement. Some popular methods include least-squares, maximum-likelihood, Bayesian, Hidden Markov Models, and artificial neural networks. In this section, together with the least-squares method, a RBF-like [7] method is presented, which is based on analyzing probability density functions (*pdf*s) of the integrated feature vector.

7.5.1 AV identification based on least-squares algorithm

One of simplest classification methods is the least-squares (LS) algorithm, which classifies an object under a minimum distance criterion. Consider the case of classification in an AV system. Let us assume that $y_1, y_2, \cdots,$ and y_n are n feature vectors in the database and denote $\boldsymbol{z}$ the feature vector representing the subject under test. The LS method solves the following problem:

$$\min_i \left\| y_i - z \right\|^2 \tag{7.9}$$

Although the LS method is very simple, its results are expected to be worse than those obtained by methods utilizing statistical information.

7.5.2 AV identification based on analyzing pdfs

Another method adopted in this chapter utilizes the *pdf*s of feature vectors. The *pdf* of a given input pattern *x* belonging to a subject may be represented by

$$g_k(x) = \frac{1}{\sigma} W\left(\frac{x - x_k}{\sigma}\right) \tag{7.10}$$

where x is a given input pattern, x_k the k^{th} pattern of subject C, W a distribution function, and σ a smoothing parameter. The average value of the *pdf*s for the "*n*" patterns of subject C can be used as the estimation of the *pdf* for this subject:

$$G(x) = \frac{1}{n\sigma} \sum_{k=1}^{n} g_k(x) \tag{7.11}$$

When Radial Basis Functions [7] are utilized as distribution functions, the *pdf* of a given input pattern x belonging to the k^{th} pattern of one subject can be estimated by (7.12), and the estimation of the *pdf* for x belonging to subject C_i is given by (7.13):

$$g_{k,i}(x) = \frac{1}{(2\pi)^{p/2} \sigma^p} e^{\frac{-\|x - x_{k,i}\|^2}{2\sigma^2}} \tag{7.12}$$

$$G_i(x) = \sum_{k=1}^{n} g_{k,i}(x) \ , \tag{7.13}$$

where $k = 1, 2, \ldots, n$, $i = 1, 2, \ldots N$; n is the number of feature vectors of subject C_i; N the number of subject classes; p the length of x; and $x_{k,i}$ the k^{th} pattern of subject C_i.

The input x is classified by using the following equation:

$$I = ind\{\max(G_1, G_2, ..., G_N)\}, \tag{7.14}$$

where *max*() and *ind*() denote max and index operations, respectively. If the objective is to identify a subject that includes several patterns, the classification is defined by.

$$R = ind\{\max(hist(I))\} \tag{7.15}$$

7.6 Experimental studies

In this section, several experiments were implemented to test the proposed methods with a database of 40 virtual subjects. After analyzing the *pdf*s of the fused feature vectors, test results were obtained for single modal and multi-modal systems, both of which are detailed in the sequel.

7.6.1 Experiment setup

To test the proposed approach, an audio and visual text-independent person recognition database was constructed. The virtual database is setup like the one in Chapter 6. For detail, please go back to read Section 6.5 in Chapter 6.

In order to compare the performance of the proposed method with that of two related single modal methods, two experiments were conducted. In these experiments, it was decided that, for each virtual subject, the length of the audio signals was 25 seconds and 20 seconds for training and 12.5 seconds and 10 seconds for testing, respectively. In addition, the codebook size for VQ was initialized to 128. Furthermore, the number of MFCC coefficients was set to 12. The following tests were conducted to evaluate the effectiveness of the proposed approach:

- LS vs. *RBF*-liked classification
- Robustness of the proposed method

7.6.2 LS vs. RBF-liked classification

The RBF-like method was compared with the LS method. The results presented in Table 7.2 indicate that the former performed much better than the latter, as the RBF-like method incorporated statistical information for classification.

Approach	AV recognition rates for best performance (Length of training time(s) / length of testing time (s))	
	25s / 12.5s	20s / 10s
LS-based	85.0%	87.5%
RBF-like	100%	100%

Table 7.2 LS *vs*. RBF-like classification

7.6.3 Robustness of the proposed method

It was shown in [18, 19, 21, 22] that the sub-system based on the visual modality outperformed the one based on the audio modality. In this experiment study, we would check the robustness of the proposed approach by feeding the algorithm with lower resolution photos and de-noised audio signals. The RBF-like classification method was employed in the system to identify the subjects under test.

As to the visual data, the resolution of face images in AV database is decreased by 4, 8 and 16 times, respectively. Moreover, audio signals were de-noised before feature extraction to increase the recognition rate, because noise affected the performance of audio-based systems. In visual sessions 1 and 2, different photos were used. In both cases, however, the lengths of audio segment for training and testing were 25s and 12.5s, respectively. The number of MFCC coefficients was set to 12. Fig. 7.5 shows the images whose effective resolution [40] was reduced by 2 and 4 times, respectively. Table 7.3[21, 59] presents a comparison of the results obtained by different approaches.



(a) Original image. (b) Image downgraded by 2. (c) Image downgraded by 4

Figure 7.4 Examples for reducing the effective resolution.

Visual Session 1				Visual Session 2			
Approach		Recognition rate		Approach		Recognition rate	
		LS	Proposed			LS	Proposed
AV	Original	85%	100%	AV	Original	87.5%	100%
	Down 4	75%	100%		Down 4	75%	100%
	Down16	60%	93%		Down16	62.5%	94%
Visual only	Original	96%		Visual only	Original	98.5%	
	Down 4	90%			Down 4	93.5%	
	Down16	71.3%			Down16	71.5%	
Audio only		67.5%		Audio only		67.5%	

Table 7.3 Comparison result under various conditions

From this table, the recognition rates of visual-based person recognition system were downgraded by reducing the effective resolution of the images. Without changing resolution, recognition rates for Session 1 and 2 were 96% and 98.5%, respectively. After image resolution was down by 4 and 16, the performance of the visual-based system was dramatically worsened, but the proposed integrated system still performed well.

From the above table, when the image resolution was down by a factor of 16, the recognition rates by using only visual data were about 71%. The rate for audio only was about 68%. The difference between them was about 3%. Both of the sub-systems

performed poorly under the condition. However, the proposed integrated AV system (fused at the feature level) achieved at least the recognition rate of 90%.

Furthermore, the proposed method based on RBF-like classification was compared with the LS method. The results in Table 6 show that the former performed much better than the later with (93-94% vs. 60-62.5%) when the visual data was greatly corrupted.

7.7 Conclusion

In this chapter, a new feature fusion method is proposed for the integration of any bi-modal biometric data and applied to a person recognition system utilizing photos and text-independent speech signals. An RBF-like classification method has also been introduced for the problem under consideration. In order to test the efficiencies of the approach presented in the chapter, different experiments were carried out. The results obtained from these experiments revealed that integrating information at the feature level by the proposed method achieved superior performance in comparison with any of the single modal systems from which it is derived. The proposed feature fusion method also produced measurable performance gains compared to methods based on intuition. Future studies include the development of algorithms that can efficiently produce a Link Matrix in an optimal sense.

8 FUSION BY GENETIC ALGORITHM AT FEATURE LEVEL

8.1 Introduction

Biometric system, both single modal and multiple modal systems, has been widely used in many applications. To solve some problems of single modal systems, various multiple modal systems have been proposed and addressed in the literature. Meanwhile, multiple modal systems have their own issues which have to be concerned in applications, for example, how to choose biometric modalities and how to effectively integrate information of the biometrics involved in systems.

As we have known, biometric traits can be integrated at the levels of sensor, feature, score and decision. Sensor fusion combines the raw data from multiple biometric sensors to generate new data from which features can be extracted; matching score level combines scores from biometrics involved to determine the identities of subjects; decision level employs majority voting or OR rules to reach the final verdict; feature level will concatenate features from all the modalities involved to form an integrated feature vector with a higher dimensionality that represents a subject's identity in a new hyperspace. Among those fusions, feature level is expected to perform better. However, it is difficult to implement as features from multiple biometric sources may not be compatible, and even if they are compatible, there is still an issue of how to effectively fuse features. The literature review has been presented in Chapter 2. For details, please go back to check the survey in that chapter.

The goal of this chapter is to devise another effective method to integrate information from two or more biometric sources. In order to test the efficiency of the proposed technique, visual-static images and text-independent speech clips are integrated with the method at feature level fusion in the experimental study for person recognition.

Fig. 8.1 shows the procedures of integrating biometric information of biometric *A* and biometric *B* in several fusion levels. Especially, the general framework for feature level fusion is specified in detail in Fig. 8.2. There exist different algorithms for the procedures of feature fusion and classification. In Fig. 8.2, the algorithms for feature fusion procedure can be genetic algorithm (GA) [59] and tabu search (TS), etc. Also, some classification methods can be employed such as least square (LS), weighted least square (WLS) [7] and probability neural network (PNN) methods.

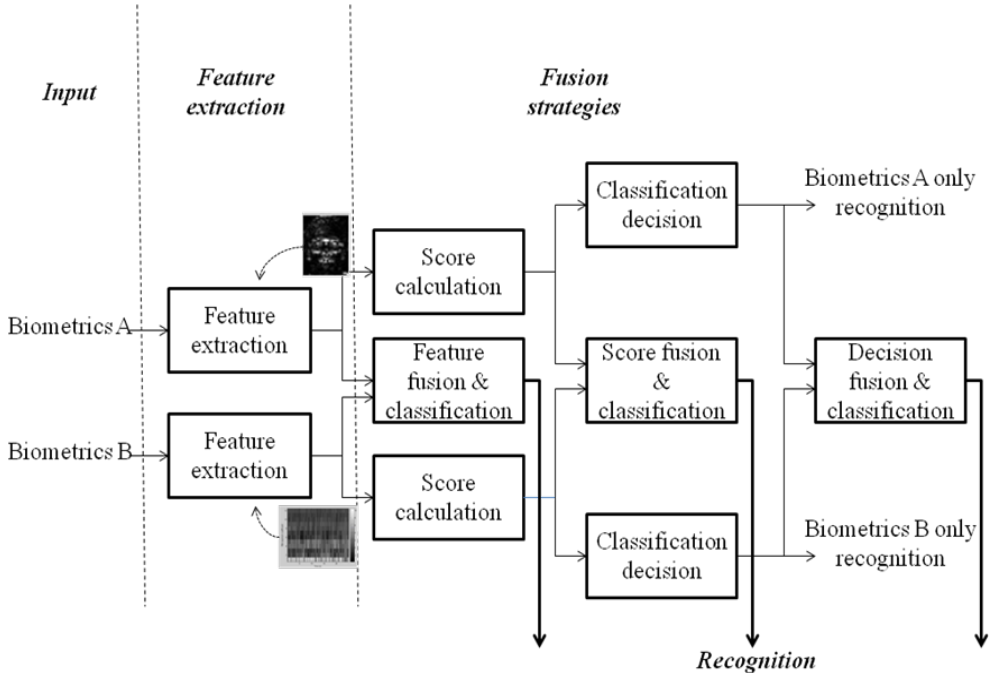


Figure 8.1 Fusion of biometric *A* and biometric *B* at various levels

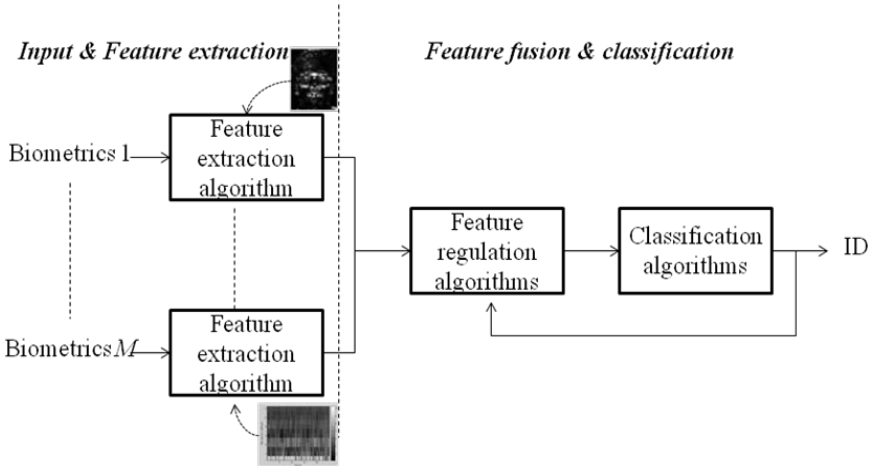


Figure 8.2 General framework for feature level fusion

In this chapter, feature fusion problem is formulated as an optimization one first. It is a more optimized algorithm to the ones in Chapter 6 & 7. As a solution strategy, GA is proposed to find its optimal solution [59], though in this case, other optimization algorithms may be as efficient as GA is. As a case study, the proposed approach is applied to integrate feature data from a virtual AV system.

The remainder of the chapter is organized as follows: Section 8.2 discusses fusion method along with GA algorithm. The idea is illustrated by integrating features from two biometric sources. Some results from experimental studies are presented and discussed in Section 8.3, and the chapter ends with concluding remarks in Section 8.4.

8.2 Proposed GA fusion method

In this section, the cost function, constraints and solution strategies are discussed. Assuming that each subject's feature vectors are extracted and normalized from M sources: D_1, D_2… and D_M, the task is to combine them so as to optimize certain performance criteria, such as computational cost and accuracy. The notations used are defined below:

M: number of modalities.

D_i: the i^{th} modality, where $i \in [1,2,.....,M]$.

N_i: number of features in modality D_i.

P_{ij}: the j^{th} component in the i^{th} normalized feature type.

α_{ij} : weight for the j^{th} component in the i^{th} feature type.

The objective for information fusion from M modalities is to obtain best performance by choosing the right weights, α_{ij}, to each feature in different modalities:

$$[\alpha_{11}P_{11}^T \quad \alpha_{12}P_{12}^T ... \alpha_{1N_1}P_{1N_1}^T \quad \alpha_{21}P_{21}^T \quad \alpha_{22}P_{22}^T ... \quad \alpha_{2N_2}P_{2N_2}^T \quad ..... \quad \alpha_{M1}P_{M1}^T \quad \alpha_{M2}P_{M2}^T ... \quad \alpha_{MN_M}P_{MN_M}^T] \qquad (8.1)$$

The weights of the one of feature types can be set to 1. As an example, suppose that there are two types of modalities in the systems, and the features in each type are equally weighted. In this case,

$$\begin{aligned} &\alpha_{11} = \alpha_{12} = ... = \alpha_{1N_1} = \alpha_1 \\ &\alpha_{21} = \alpha_{22} = ... = \alpha_{2N_2} = \alpha_2 = 1 \end{aligned} \qquad (8.2)$$

One can then select α_1 such that a performance measure is optimized. Once α_1 is obtained, the integrated feature vector is then

$$[\alpha_1 P_{11}^T \quad \alpha_1 P_{12}^T \quad ..... \quad \alpha_1 P_{1N_1}^T \qquad P_{21}^T \quad P_{22}^T ..... \qquad P_{2N_2}^T] \qquad (8.3)$$

The following remarks can be made about the solutions of the proposed problem:

- Random search is a method aimed at reaching an acceptable solution. The eventual solution is obtained simply by taking the choice of α_{ij} that is used to fuse the information and yields the best performance of the multimode system

among the randomly tested candidate solutions. Such a strategy may take a long time to achieve the suitable weights α_{ij} for the system.

- Gradient search is probably the easiest way to find the extreme. Visually the strategy of a gradient search is to pick the direction that is steepest uphill (or downhill) from the guess, and move in that direction until the graph levels out. Mathematically, in each step, the gradient is used as the direction of search. The process is repeated until the gradient approaches zero. Therefore, such a method attempts only to find a local maximum or minimum.
- Genetic algorithm (GA) [59] is a search technique for seeking optimal solutions. It is based on the principle of natural selection to simulate the search problem. The search starts with a randomly generated initial population. At each step, the algorithm selects individuals randomly from the current population to be parents to produce children for the next generation. Over successive generations, the population will evolve toward one containing the optimal one.

GA is employed in this chapter to find the optimal solution for biometric fusion problem, and there are several building blocks in GA: initialization, selection, reproduction and termination. Initially a set of individual solutions are randomly generated to form the initial population, whose size typically contains hundreds of possible solutions and covers a wide range of the search space. During each successive generation, a new generation is bred after selecting a portion of the existing population with a fitness function, which rates the fitness of each solution and preferentially selects the better individuals. Roulette wheel selection is one of well-studied methods. Its fitness

level is used to associate a probability of selection with each individual chromosome. If f_i is the fitness of individual i in the population, its probability of being selected is,

$$p_i = \frac{f_i}{\sum_{j=1}^{N} f_j} \tag{8.4}$$

where N is the number of individuals in the population.

Crossovers and mutation are employed to generate children from “parents” selected for mating with the procedure [59] similar with the one outlined above. A new solution is created which typically shares many of the characteristics of its "parents". Such process continues until a new population of solutions of appropriate size is generated.

The following steps illustrate the core of GA algorithm [59]:

Step 1: Randomly choose the initial population;

Step 2: Evaluate the fitness of each individual in the population;

Step 3: Repeat the following until a new population is generated:

1) Select individuals based on, say, Roulette wheel procedure;

2) Breed new generation by applying crossover and mutation;

Step 4: Repeat Steps 2 and 3 until the solution is not improved more.

There exists a variety of variations to the procedure outlined above. Two-point crossover algorithm creates two children by exchanging genes of pairs of parents in the current population. Occasional mutation makes small random changes to the individuals in the population. Meanwhile, a way to speed up the convergence of the algorithm is to keep a number of the best solutions from one generation to another. Another way of

speeding up is to have a set of initial guesses based on the physical constraints of the problem. For fusion, the following steps are applied to obtain the weights α_{ij}:

Step 1: Assumed the information vectors are equally weighted within any one type of modalities;

$$\alpha_{i1} = \alpha_{i2} = ... = \alpha_{iN_i} = \alpha_i \qquad for \quad i = 1,2,....., M \tag{8.5}$$

where i is for the i^{th} modality, N_i is the number of information vectors in the i^{th} modality D_i, which are to be fused with others from other modalities.

Step 2: Use α_i to be the center of the ranges for unknown α_{ij} and apply the GA algorithm to find α_{ij} .

$$\alpha_i - D_i \le \alpha_{ij} \le \alpha_i + D_i \tag{8.6}$$

where threshold D_i is given according to experiments, and $i = 1,2,....., M$.

In Step 1, the values may be determined by a simple optimization procedure as the number of parameters involved in this stage is relatively much smaller. Furthermore, if only two modalities are involved, one unknown α_1 needs to be determined in this step. In such a case, the Golden Ratio method, which is very efficient for such an application, can be applied to find the value of α_1.

In the case of feature level fusion, once the fused feature vectors are obtained with the proposed method, these will be used for classification (Figure 1). Among various classification methods, Probability Neural Network (PNN) and Weighted Least-Square (WLS) algorithm are viable candidates.

The activation function in PNN is derived from an estimation of probability density functions (*pdf*) based on a set of training set. The *pdf* of input x belonging to subject C_i can be estimated by (8.7) and classified by (8.8):

$$g_i(x) = \frac{1}{(2\pi)^{p/2}\sigma^p} e^{\frac{-\|x-x_i\|^2}{2\sigma^2}} \tag{8.7}$$

$$ind = \min_i(g_i(x)) \tag{8.8}$$

where $i = 1, 2, \ldots N$, N the number of subject classes, p is the length of x, σ the smoothing parameter, $x_{,i}$ the pattern of subject C_i.

Least square method is used to compute estimations of parameters and to fit a set of data. There exist several variations, and a more sophisticated version is WLS, which often performs better because it can emphasize the importance of each observation [7]. The idea is to assign to each observation a weight that reflects the uncertainty of the measurement. The error vectors ΔF_i in WLS can be defined as

$$\Delta f_j = f_j - x_j \tag{8.9}$$

$$\Delta F_i = [\Delta f_1, \cdots, \Delta f_M] \tag{8.10}$$

where f_j is the feature of training subjects, x_j is the j^{th} feature vector representing the subject under test, $j = 1, 2, \ldots M$, and M is the number of feature vectors for each subject. Furthermore, $i = 1, 2 \ldots N$, where N is the number of subject classes. Let the weights $\beta = [\beta_1, \beta_2, \cdots, \beta_M]$, the objective function can be defined as

$$\min_i (\beta * \Delta F_i)^T (\beta * \Delta F_i) \tag{8.11}$$

Let

$$\Gamma = \begin{bmatrix} \beta_1^2 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \beta_M^2 \end{bmatrix} \tag{8.12}$$

Then (8.11) is rewritten as

$$\min_i (\Delta F_i)^T \Gamma (\Delta F_i) \tag{8.13}$$

In experiments, we find that PNN produces similar results to WLS. However, the WLS algorithm does not suffer as much the problem of "curse of dimensionality", in comparison to PNN. Also, WLS algorithm is much simpler to implement.

8.3 AV Case Studies

An AV system using the proposed method is shown in Fig.8.3. The database consisted of the audio part and face (visual) part with 40 subjects. The virtual database in these experiments is setup as the one in Chapter 6 & 7. For details, please check the previous chapters.

After audio and visual data were fused using GA, the integrated feature vectors were fed to PNN or WLS to produce test results. For a comparison study, results from both single and multiple modal systems are detailed next.

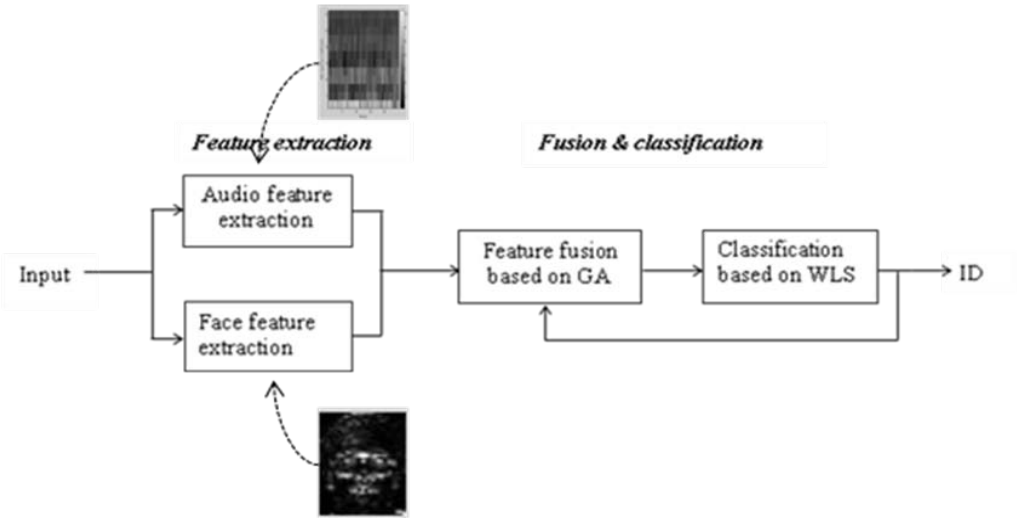


Figure 8.3 AV feature level fusion

In order to compare the performance of the proposed method with that of the two related single modal methods, several experiments were conducted. In these experiments, it was decided that, for each virtual subject, the length of the audio signals was 25 seconds for training and 12.5 seconds for testing, respectively. In addition, the codebook size for VQ was initialized to 128. Furthermore, the number of MFCC coefficients was set to 12. In the GA algorithm, the two-point crossover method was used with crossover rate 0.8, the elite size was 2, and the mutation rate was set as 0.002.

From Table 8.1, the best performances of PGE method were 96.0% and 98.5% for original data session 1 and 2, respectively. These results indicate that PGE was very suitable for recognizing persons. The Gabor wavelet representation facilitates recognition without correspondence in the PGE algorithm, because it captures the local structure corresponding to spatial frequency, spatial localization, and orientation selectivity.

Also, shown in Table 8.1 are some testing results for text-independent audio-based single modal person recognition. The experimental result suggested that the recognition rate was improved from 47.5% to 67.5% after audio signals for both testing and training were de-noised. This is expected, as the performance of speaker recognition heavily relies on the clearness of audio signals, and the de-noising procedure reduces the deleterious effect of background noise.

The proposed fusion method was compared with the single modal systems under the classification methods of the PNN and WLS algorithms. The results from the PNN and WLS methods were identical, which was expected. Thus, in the subsequent experiments, we used the WLS method to classify the fused features of visual and audio

signals. And in training visual session 1, the maximum value for the dimension of the fused feature for one subject was *M*, where $M = 128x12+6x239 = 2970$ when all of the eigenvectors for visual features have been employed. The results presented in Table 8.2 indicate that the former performed much better than the latter.

It was shown the sub-system based on the visual modality outperformed the one based on the audio modality in [19, 21, 22, 24]. In this experiment study, we would also check the robustness of the proposed approach by feeding the algorithm with lower resolution photos and de-noised audio signals in order to obtain closer recognition results from both of the single modal systems.

As to the visual data, the resolution of face images in AV database is decreased by 4 and 8 times, respectively. Moreover, audio signals were de-noised before feature extraction to increase the recognition rate, because noise affected the performance of audio-based systems. In visual sessions 1 and 2, different photos were used. In both cases, however, the lengths of audio segment for training and testing were 25s and 12.5s, respectively. The number of MFCC coefficients was set to 12. Table 8.1 presents a comparison of the results obtained by different approaches.

Visual session 1			Visual session 2		
Approach	Recognition rates		Approach	Recognition rates	
AV fusion	Original visual	100%	AV fusion	Original visual	100%
	Down 4 visual	100%		Down 4 visual	100%
	Down 8 visual	97.5%		Down 8 visual	97.5%
Visual only	Original visual	96.0%	Visual only	Original visual	98.5%
	Down 4 visual	90.0%		Down 4 visual	93.5%
	Down 8 visual	81.3%		Down 8 visual	83.0%
Audio only	Original audio	47.5%			
	Denoised audio	67.5%			

Table 8.1 Comparison result under various conditions

From this table, the recognition rates of visual-based system were downgraded by reducing the effective resolution of images. Without changing the resolution, recognition rates for Session 1 and 2 were 96% and 98.5%, respectively. After image resolution was down by 4 and 8, the performance of the visual-based system was dramatically worsened to 90% and 81.3% for visual session 1 and to 93.5% and 83.0% for visual session 2, respectively; however the proposed integrated AV system still performed well.

Because the single modal recognition system with face only information performed much better than the voice only modal system, the features from the visual part will gain more weight than those from audio part in the AV system. In the tests performed in this section, weights for the audio part were assumed to be equal to 1, which only leaves the

weights for the visual part remaining unknown. After employing golden ratio method, the initial values of α_2 for visual parts are obtained and listed in Table 8.2. Meanwhile, each individual feature has a different influence in person recognition. After applying GA method to search the parameters, the weights for visual features were obtained for the integration of the features extracted from visual and audio signals (Table 8.2). This illustrates the relative importance of each coefficient in person recognition.

	α_2	α_{21}	α_{22}	α_{23}	α_{24}	α_{25}	α_{26}
Original	22.01	23.6742	22.6813	22.0118	22.0307	23.9000	20.8905
Down 4	21.18	20.5679	20.2311	21.4008	23.5144	21.2964	21.1230
Down 8	21.80	22.4153	23.7919	22.7807	21.6588	20.4468	20.2479

Table 8.2 Weights for visual part in the virtual AV system

8.4 Conclusion

In this chapter, a feature fusion method is proposed for the integration of multi-modal biometric data, and as a special case, it is applied to a person recognition system utilizing photos and text-independent speech signals. The weights of individual feature vectors are obtained with a GA algorithm and subsequently used in a classification procedure for person recognition. In order to test the effectiveness of the proposed approach, a number of experiments were carried out. The results obtained from these experiments revealed that integrating information through the proposed method achieved much better performance and maintained much more robust results in comparison with any of the single modal systems from which it was derived.

9 FUSION BY SIMULATED ANNEALING AT FEATURE LEVEL

9.1 Introduction

Biometric systems have been attracted the attention from the public because of some high profile applications, such as FBI Integrated Automated Fingerprint Identification Systems (IAFIS), Criminal Scene Investigation (CSI) science labs and US-VISIT program. In addition to the usages linked to criminal investigation, biometric identification and authentication systems have also been used in many other applications such as entertainment and banking.

A single modal based biometric system only employs one biometric modality, while a multi-modal system utilizes at least two biometrics. Single modal systems are typically composed of four basic modules: sensor module, feature extraction module, matching score module, and decision module (Fig. 9.1).

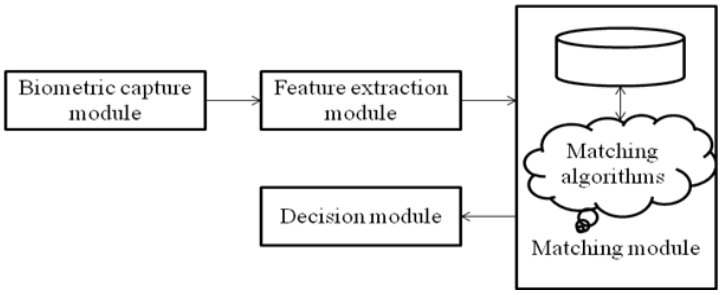


Figure 9.1 Modules of single modal biometric systems

Single modal systems have shown some disadvantages in biometric research, they become more susceptible to noisy sensory data, restricted degrees of freedom, enrollment failure, spoof attacks and mismatch between training and testing environments. The use

of multi-modal biometrics has the potential of improving greatly performance of single modal systems by taking advantages of various modality traits. An additional advantage of using multi-modal systems is that it is more difficult for identity thefts to steal multiple biometric traits from a true user.

Methods of information integration can be categorized as either pre-mapping or post-mapping. More specifically, information extracted from multiple biometric traits can be integrated at levels of sensor, feature, score and decision.

In this chapter, a stimulated annealing (SA) algorithm [45] is proposed for feature level fusion. Simulated annealing can regulate the contribution of features extracted from different modalities to obtain an integrated feature vector, which is in turn used to classify the subject under test. The proposed method is applied to integrate feature information from a virtual Audio-Visual system consisting of 40 subjects.

The rest of the chapter is organized as follows. Section 9.2 presented the details of the proposed method. As a case study, results of an experimental study using the method are reported in Section 9.3. Concluding remarks are given in Section 9.4.

9.2 Fusion based on simulated annealing

9.2.1 Fusions

As stated above, biometric data presented from multiple biometric traits can be integrated at different levels. The proposed method in this chapter can be applied not only for feature level fusion in AVTI systems, but also for other level fusions and other multimode biometric systems.

Fig.9.1 shows a general framework for feature level fusion for M biometric modalities. In this figure, different algorithms may be utilized for feature extraction,

feature fusion and classification. Regulation algorithms for feature fusion determine the contribution of different features extracted from different modalities. Various classification methods such as Weighted Least Squares (WLS), Bayesian Classifier and Probability Neural Network (PNN) can be applied to determine the identity of a subject. Optimal searching strategies such as Genetic Algorithm (GA), Simu1ated Annealing (SA) [45], and Tabu Search (TS) may help to obtain better overall system performance.

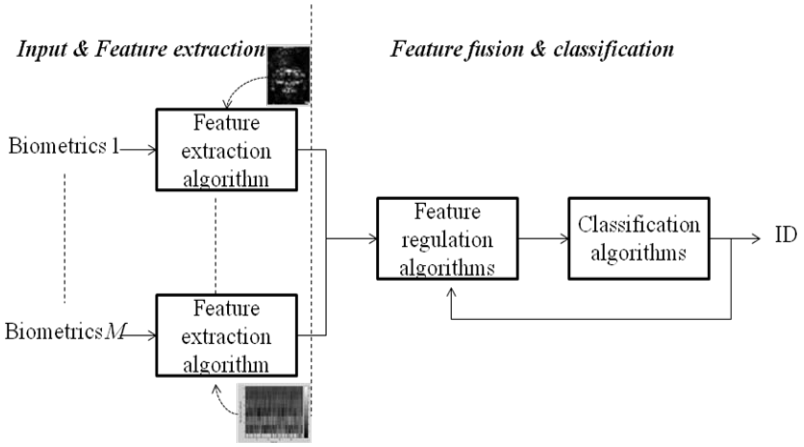


Figure 9.2 General framework for feature level fusion

9.2.2 Proposed model of biometric fusion

In this section, feature fusion is a case for the proposed model of biometric fusion. Such fusion problem is formulated as an optimization one first. The cost function, constraints and solution strategies are discussed in detail later. As one of the solution strategies, Simulated Annealing (SA) algorithm is adopted to find its optimal solution [45]. The method developed is then applied to fuse audio and visual biometric feature vectors. SA algorithm helps to regulate the contribution of each individual biometric modality to a concatenated feature vector.

Let us assume that each subject's feature vectors are extracted from *M* sources: D_1, D_2… and D_M. The task is to combine them to optimize certain performance criteria, such as computational cost and accuracy. The notations used are defined below:

M: number of modalities.

D_i: the i^{th} modality, where $i \in [1,2,.....,M]$.

N_i: number of features in modality D_i.

P_{ij}: the j^{th} component in the i^{th} feature type.

α_{ij} : weight for the j^{th} component in the i^{th} feature type.

The objective for information fusion of *M* modalities is to minimize a cost function by choosing the weights, α_{ij} :

$$\begin{aligned}&[\alpha_{11}P_{11}^T \quad \alpha_{12}P_{12}^T ... \alpha_{1N_1}P_{1N_1}^T \quad \alpha_{21}P_{21}^T \quad \alpha_{22}P_{22}^T ... \quad \alpha_{2N_2}P_{2N_2}^T \quad .....\\ &\alpha_{M1}P_{M1}^T \quad \alpha_{M2}P_{M2}^T ... \quad \alpha_{MN_M}P_{MN_M}^T]\end{aligned} \tag{9.1}$$

The weight of one of feature types can be set to 1. As an example, suppose that there are two types of modalities in the systems, and the features in each type are equally weighted. In this case,

$$\begin{aligned}&\alpha_{11} = \alpha_{12} = ... = \alpha_{1N_1} = \alpha_1\\ &\alpha_{21} = \alpha_{22} = ... = \alpha_{2N_2} = \alpha_2 = 1\end{aligned} \tag{9.2}$$

The integrated feature vector can be changed to

$$[\alpha_1 P_{11}^T \quad \alpha_1 P_{12}^T \quad ..... \quad \alpha_1 P_{1N_1}^T \quad P_{21}^T \quad P_{22}^T ..... \quad P_{2N_2}^T] \tag{9.3}$$

9.2.3 SA regulation algorithm

The following remarks can be made about the proposed method:

- Random search [30, 54] over the domain of interest is a method aimed at reaching an acceptable solution. The eventual solution is obtained simply by taking the choice of α_{ij} that is used to fuse the information and yields the best performance of multimode systems among the randomly tested candidate solutions. The disadvantage of random search is that such a searching strategy may take a longer time to achieve suitable weights α_{ij} for a given system.
- Gradient search [30,54] is one of easy ways to find extreme values of functions for which their gradient can be computed. Visually the strategy of a gradient search is to pick the direction that is steepest uphill (or downhill) from the current position, and move in that direction guided by the gradient, until the graph levels out. The process is repeated until the gradient approaches zero. Such a method in general suffers from trapping in local extreme values.
- Genetic algorithm (GA) [59] is a search technique for seeking global optimal solutions. It is based on the principle of natural selection to simulate the search problem. The search starts with a randomly generated initial population. At each step, the algorithm selects individuals randomly from the current population to be parents to produce children for the next generation. Over successive generations, the population will evolve toward one which may contain the optimal one. This method is computationally more intensive.
- Simulated annealing (SA) [45] is a Monte Carlo approach for minimizing multivariate functions. In fact, SA is originally derived from the physical process of heating and then slowly cooling a substance; and when it cools down, a strong crystalline structure is obtained with a minimum energy. It is a

powerful technique used to solve nonlinear combinatorial optimization problems. It can incorporate a probability function to accept or reject new solutions to avoid local minima. Meanwhile, it does not need large computer memory. By employing a properly selected cooling strategy, SA can search global optimal solutions rapidly. In addition, SA is a flexible algorithm capable of handling problems with a mix of continuous and discrete data sets.

The notations used in SA are defined below:

- W: States or solution (i.e. weights for feature concatenation in feature fusion)
- E: System Energy (i.e. Objective function value or cost function value)
- T: System Temperature (for cooling schedule)
- T_0: Initial temperature
- T_f: Final temperature
- Δ: Difference in system energy between two solutions
- σ: Cooling rate

Stochastic techniques which allow acceptance of reversals in solutions have long been practiced to improve greedy approaches. SA is adopted in this research to solve the biometric fusion problem because it is a better established stochastic technique. The SA algorithm is composed of the following four basic components:

- A representation of possible problem solutions in a search space;
- A generator of random changes in a solution that will allow reaching all feasible results and is easy to compute;
- A cost function to measure any given solution;

- A cooling schedule to anneal the problem from a random solution to a good, frozen placement. Specifically, it includes some parameters during the cooling procedure, such as initial temperature T_0, final temperature T_f, and temperature rate of change, also called cooling rate σ.

Among the four components of SA algorithm, the cooling schedule needs to be paid more attention because the choice of the parameters can decide the efficiency of SA, which concerns about the quality of global extremes and the number of iterations of this procedure. Initial temperature T_0 can be decided by (9.4) according to [45].

$$T_0 = \frac{\overline{\Delta V}^{(+)}}{\ln(1/X_0)} \tag{9.4}$$

where $\overline{\Delta V}^{(+)}$ is the average increase in cost for a certain number of random transitions; X_0 is the rate of acceptance, which normally ranges between 0.8 and 0.95. Generally speaking, the final temperature T_f, can be used to determine the stopping criteria of SA in practice, which means that the procedure stops at the optimal point T_f where the improvements in the objective function become so small that it can be ignored. Meanwhile, the rate of cooling, σ, affects directly the number of iterations required at each temperature level. Usually, $\sigma \in [0.50, 0.99]$ [45].

As a matter of fact, in a natural process, the system cools down logarithmically, but that is a time- consuming procedure. Therefore, many simplified methods have been proposed for some real-world applications such as travelling salesman problem. One of popular cooling models is:

$$T_{k+1} = \sigma T_k \tag{9.5}$$

where T_k is the current temperature and T_{k+1} is the next one.

The algorithm starts from a valid solution and generates new one randomly, and then calculates the associated cost function. The annealing process starts at high temperature. Once a new result is randomly chosen and its cost is calculated, the difference Δ in cost is determined. If (9.6) is satisfied, which means the cost of the new solution is lower, this solution is accepted.

$$\Delta = E_{k+1} - E_k \leq 0 \tag{9.6}$$

where Δ is the difference of the results of cost functions, and E_{k+1} and E_k are new cost and current cost, respectively. This action forces the system toward a point corresponding to an extreme point.

However, there are many local minima in most optimization problems, therefore, the optimization algorithm is often trapped in a local minimum if (9.6) is the only constraint to the SA algorithm. Unlike greedy search, SA will not only accept results which lead to better solutions, but also allow a probabilistic acceptance reversal. To avoid getting stuck in a local extreme, an increase of the cost function is accepted with a certain probability P which is defined by Boltzman's equation in (9.7) [45]:

$$P = e^{\frac{\Delta}{T}} > random() \qquad \text{when} \quad \Delta > 0 \quad \textit{and} \quad random() \in [0,1) \tag{9.7}$$

where T is temperature, which is gradually decreased during the process.

The following steps illustrate the steps of SA and Fig.9.2 outlines its flowchart:

- Choose a random W_K, select the initial system temperature, and specify the cooling schedule
- Evaluate $E(W_K)$
- Perturb W_K to obtain a neighboring state (W_{K+1})

- Evaluate $E(W_{K+1})$
- If $E(W_{K+1}) < E(W)$, W_{K+1} is the new current solution
- If $E(W_{K+1}) > E(W)$ *and* probability $e^{(-\Delta/T)} < random()$, then accept W_{K+1} as the new current solution with a probability $e^{(-\Delta/T)}$ where $\Delta = E(W_{K+1}) - E(W_K)$ and
- Reduce the system temperature according to the cooling schedule
- Terminate the algorithm.

In an implementation, the stop criterion for the SA procedure needs to be given. Listed below are some ideas:

- The solution is trapped in an extreme; *or*
- The value of temperature has reached a given threshold; *or*
- The total number of iterations reaches a limit; *or*
- The running time reaches a limit.

In the case of feature level fusion, once the fused feature vectors are obtained with the proposed method, they will be used for classification (see Fig. 9.1). Among various classification methods, Probability Neural Network (PNN) and Weighted Least-Square (WLS) algorithm are viable candidates.

The activation function in PNN is derived from an estimation of probability density functions (*pdf*) based on a set of training set. The *pdf* of input z belonging to subject C_i can be estimated by (9.8) and classified by (9.9):

$$g_i(z) = \frac{1}{(2\pi)^{p/2}\sigma^p} e^{\frac{-\|z-z_i\|^2}{2\sigma^2}} \tag{9.8}$$

$$ind = \min_i (g_i(z)) \tag{9.9}$$

where i = 1, 2, … N, N is the number of subject classes, p the length of z, σ the smoothing parameter, and $z_{,i}$ the pattern of subject C_i.

WLS method [7] is to assign to each observation a weight that reflects the importance of the measurement. The objective function of WLS is described as follows:

The error vectors can be defined as

$$\Delta f_j = f_j - z_j \tag{9.10}$$

$$\Delta F_i = [\Delta f_1, \cdots, \Delta f_M] \tag{9.11}$$

where f_j is the feature of training subjects, z_j is the j^{th} feature vector representing the subject under test, j = 1, 2 … M, and M is the number of feature vectors for each subject. Furthermore, i = 1, 2 … N, where N is the number of subject classes. Let

$$\beta = [\beta_1, \beta_2, \cdots, \beta_M] \tag{9.12}$$

The objective function can be defined as

$$\min_i (\beta * \Delta F_i)^T (\beta * \Delta F_i) \tag{9.13}$$

Let

$$\Gamma = \begin{bmatrix} \beta_1^2 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \beta_M^2 \end{bmatrix} \tag{9.14}$$

Then (9.13) is rewritten as

$$\min_i (\Delta F_i)^T \Gamma (\Delta F_i) \tag{9.15}$$

In experimental studies we find that PNN produces similar results to WLS. However, WLS algorithm does not suffer as much the problem of "curse of dimensionality", in comparison to PNN. Also, WLS is much simpler to implement.

9.3 A case study: audio-visual biometric system

This section describes a case study for the proposed SA fusion method. A virtual database is used to test the algorithm, which is composed of static people face images and speech clips of 40 subjects. Briefly speaking, the database used in this section includes audio part and face part. The visual part of the database was from the AT&T (formally Olivetti) database. Especially, in audio part of the database, training set included text-independent speeches obtained using the same microphone from the public speeches of various topics in noisy backgrounds and a testing set with 40 voices of the same subjects also addressing different topics. A virtual subject was constructed by assigning a speech subject to a face subject. The database setup will be the same with the one in previous chapters, and two data sessions will be employed in the following experiments. For the details of database session 1 and 2, please refer to Chapter 6

9.3.1 AV feature extraction

No matter which level fusion the multi-modal biometric system applies, feature extraction module of each individual modality is one of the most essential steps, because the performance of systems strongly relies on the accurate extraction of biometric features from original biometric sources. For example, in a speaker recognition system, in theory, it should be possible to recognize speakers directly from waveforms. However, because of the large variability of speech signals, it is a good idea to extract essential

features from speech signals. This is also true for face recognition and any other biometric recognition systems.

As a case study, an Audio-visual (AV) system composed of static face images and text-independent speeches is investigated in this research. In the AV system under investigation, visual features are extracted by the Pyramidal Gabor wavelet with the Eigenface (PGE) algorithm [20] and audio features are extracted by the Mel Frequency Cepstrum Coefficients (MFCCs) algorithm.

It is known that there are many advanced methods to extract face features. In this case study, PGE method is employed because 1) the involvement of Gabor wavelets benefits face recognition and makes it more robust against variations from lighting condition and viewing direction; 2) to save computational cost and memory space, a pyramidal structure is used in the spatial domain to avoid the procedures of Fourier transform and inversed Fourier transform, which are often utilized in general 2-D Gabor wavelet based face recognition methods.

The central task of a typical audio-based feature extraction procedure is to parameterize speech signals into a sequence of feature vectors that are less redundant for statistical modeling. Spectral features, such as Linear Predictive Cepstrum Coefficients (LPCCs) or Mel Frequency Cepstrum Coefficients (MFCCs) [3] have been widely used. In this section, the procedure of MFCCs is applied to obtain audio feature vectors. Meanwhile, when considering the amount of feature sets for each subject, MFCCs must be compressed. Vector quantization (VQ) [35] is one of the popular algorithms utilized for this purpose.

9.3.2 Experiment

In order to compare the performance of the proposed method with that of two single modality systems involved, several experiments were conducted. In these experiments, it was decided that, for each virtual subject, the length of the audio signals was 25 seconds for training and 12.5 seconds for testing, respectively. In addition, the codebook size for VQ was initialized to 128. Furthermore, the number of MFCC coefficients was set to 12. In the SA algorithm, the initial temperature is set as 100; also, the termination of the algorithm is set as 100 times of iteration.

From Table 9.1, the best performances of PGE method were 96.0% and 98.5% for original data session 1 and 2, respectively. These results indicate that PGE was very suitable for recognizing persons. The Gabor wavelet representation facilitates recognition without correspondence in PGE algorithm, because it captures the local structure corresponding to spatial frequency, spatial localization, and orientation selectivity. As a result, the Gabor wavelet representation of face images is robust to deal with the variations caused by illumination condition, viewing direction, poses, facial expression changes and disguises.

Also, shown in Table 9.1 are some testing results for text-independent audio-based single modal person recognition. The experimental result suggested that the recognition rate was improved from 47.5% to 67.5% after audio signals for both testing and training were de-noised. This is expected, as the performance of speaker recognition heavily relies on the clearness of audio signals, and the de-noising procedure reduces the deleterious effect of background noise.

The result obtained from using SA regulation method was compared with those of single modal systems. The results presented in Table 9.1 indicate that the former

performed much better than the latter, which is expected. It was shown in [12] that the sub-system based on the visual modality outperformed the one based on the audio modality. In this experiment study, we would also check the robustness of the proposed approach by feeding the algorithm with lower resolution photos and de-noised audio signals in order to obtain closer recognition results from both of single modal systems.

As to the visual data, the resolution of face images in the AV database is decreased by 4 times. Moreover, audio signals were de-noised before feature extraction to increase the recognition rate, because noise affected the performance of audio-based systems. In visual sessions 1 and 2, different photos were used. In both cases, however, the lengths of audio segment for training and testing were 25s and 12.5s, respectively. The number of MFCC coefficients was set to 12. Table 9.1 presents a comparison of the results obtained by different approaches.

Visual session 1			Visual session 2		
Approach	Recognition rates		Approach	Recognition rates	
AV fusion	Original visual	100%	AV fusion	Original visual	100%
	Down 4 visual	100%		Down 4 visual	100%
Visual only	Original visual	96.0%	Visual only	Original visual	98.5%
	Down 4 visual	90.0%		Down 4 visual	93.5%
Audio only	Original audio	47.5%			
	Denoised audio	67.5%			

Table 9.1 Comparison result under various conditions

From this table, the recognition rates from the visual-based person recognition system were downgraded by reducing the effective resolution of the images. Without changing the resolution, recognition rates for data sessions 1 and 2 were 96% and 98.5%, respectively. After image resolution was down by 4, the performance of the visual-based system was worsened to 90% for visual session 1 and to 93.5% for visual session 2, respectively; however the proposed integrated AV system still performed well.

Figure 9.3 illustrates the SA results for visual data session 1, which means six out of the 10 images of each subject were randomly picked to construct the visual training set 1, and the remaining formed the related visual testing set 1. Meanwhile, the lengths of audio segment for training and testing were 25s and 12.5s, respectively. In this figure, The cost function is defined using recognition error rate, and it showed that after about 45 iterations, the system reaches a steady state solution. In the figure, the best point values are the values of weights α_i (i = 1, 2… 6) produced by SA. It indicates the contributions of visual features, while assuming the weights of audio features set to 1.

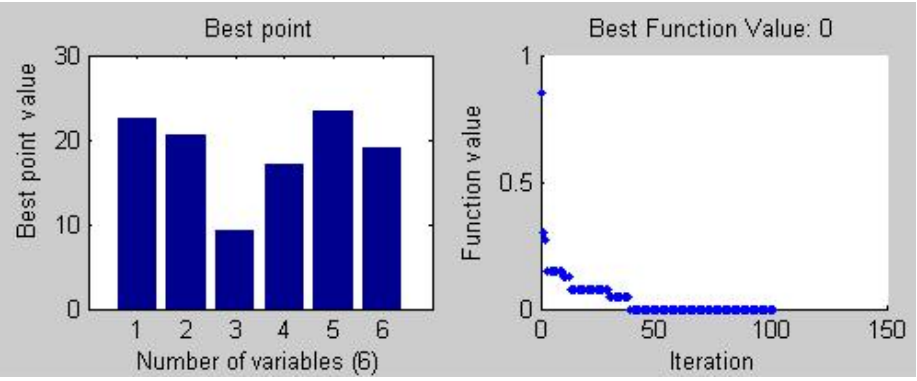


Figure 9.3 SA results

9.4 Conclusions

In this chapter, a feature fusion model has been proposed for the integration of multi-modal biometric data, and the SA regulation algorithm has been applied to determine contributions of different modalities for biometric recognition. There have been seldom algorithms and solutions for feature fusion of AV systems due mainly to the following issues: 1) the difficulty of sequencing incompatible features such as audio and visual signals, and 2) the curse of dimensionality when combining biometric information. With the proposed method, the above issues have been successfully addressed. As a case study, the proposed algorithm has been applied to a person recognition system utilizing photos and text-independent speech signals. The weights of individual feature vectors have been obtained with the SA fusion algorithm and subsequently fed to a WLS-based classification module to identify the subjects under test. A number of experiments have been performed to test the effectiveness of the proposed approach. The results obtained from these experiments suggest that integrating information with the proposed method can achieve much better performance in comparison to any of the single modal systems from which it is derived.

10 FUSION AT SCORE LEVEL

10.1 Introduction

Depending on different circumstances and applications, biometric measurements and analysis are used for identification or verification purposes. In order to implement biometric specific purposes, the biometric community has done a great deal of work in adapting knowledge and technologies from a variety of specialized areas, such as statistics, pattern recognition, artificial intelligence, image processing, and medical science. Those mature fields have supported biometric science with optimized tools, and made it develop much faster. But biometric study is still a fertile area for future work.

Relying on the number of sources it employs, there are two types of biometric systems: single modal and multiple modal systems. Single modal biometric system has been applied in many areas in practice, but it suffers from some intrinsic disadvantages and is not strong enough to handle some problems. Multiple modal biometrics is the process of combining information from different sources in order to compensate for the limitations of a single modal system. Therefore, multiple modal systems may achieve an enhanced performance in most cases. In the previous chapters, feature level fusion has been discussed. And this chapter will consider score level fusion and propose simple methods based on Golden-Ration algorithm [39]. As a case study, the proposed method GR has been employed in our AV database, which consists of audio and visual information with 40 subjects.

Generally, biometric scientists / researchers prefer to score level fusion for multiple modal biometric systems, due to the ease in fusion. And there exists a strong theoretical basis for biometric fusion in score level. Many researchers have demonstrated that fusion is effective that the fused scores provide much better discrimination than the individual scores.

Numerous proposals in literature have been made for score level fusion. Each method contains its own advantages and disadvantages. Selecting the most effective fusion techniques depends on practical needs, such as accuracy requirements, and availability of biometric data and so forth. However, it is still a challenge to combine matching scores from different biometric sources, because their contributions are not same. Among the algorithms evaluated, Golden-Ratio (GR) methods have been proposed in this chapter, and have been found to be effective and very simple.

The following lists several main papers and results for score level fusion as some examples. For more details, please check Chapter 2.

- In 1998, Kittler et al [29] tested several classifier combination rules on a multiple modal biometric system, which consists of frontal face, face profile, and voice biometrics with 37 subjects in the database. They found that the “sum” rule outperformed the product, min, max, and median rules, due to its resilience to errors in the estimation of the densities.
- In 1999, Ben-Yacoub et al [60] evaluated combination rules of score levels to a system including three face and voice modalities using a database of 295 subjects. They found that a support vector machine and Bayesian classifier achieved almost the same performances.

- In 2005, Jain et al [6] applied the sum of scores, max-score, and min-score fusion methods, when fusing the normalized scores from face, fingerprint, and hand geometry biometrics with a database of 100 subjects. They found that optimizing the weights of each biometric on a user-by-user basis outperforms generic weightings of biometrics.

In this chapter, a golden ratio algorithm (GR) is modified for score level fusion. It can regulate the contribution of scores from different modalities to obtain an integrated score value, which is in turn used to classify the subject under test. The method has been tested to integrate matching scores from a virtual AV system consisting of 40 subjects.

The rest of the chapter is organized as follows. Section 10.2 presented the details of the method. As a case study, results of an experimental study are reported in Section 10.3. Concluding remarks are given in Section 10.4.

10.2 Proposed Methods

As stated in Chapter 5 (see Fig 10.1), there are four modules when implementing a single modal biometric system. When mapping to a multiple modal system, biometric fusion can be done in four levels too. Once the feature vectors from each biometric modal have been constructed, they are passed to their individual matching score algorithms, which attempt to match them against previously captured templates. The individual matching scores are then combined to form a result, from which a decision may be made (see Figure 10.1).

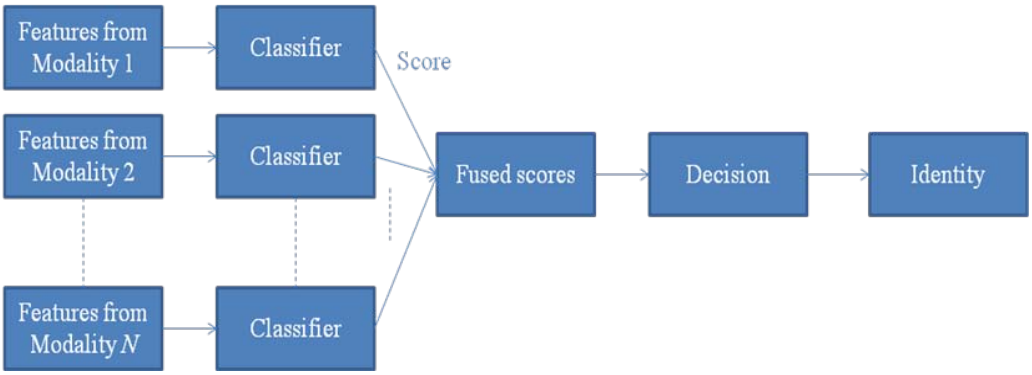


Figure 10.1 Procedures of score level fusion for multiple modal biometrics

Integration done at the matching score level is also known as fusion at the measurement level or confidence level. The biometrics modality provides an opinion on each possible decision by the approaches that are either non-homogeneous or homogeneous [33, 51]. For example, in some AV systems, the opinion from audio part provides the opinion in terms of a likelihood measure, while the visual part gives its opinion in terms of distances. Before being fused in the score level, the opinions about the subject from different modalities will be commensurate; this can be accomplished by mapping the output of each modality to the [0, 1] interval where 0 indicates the lowest opinion and 1 the highest opinion.

It is relatively easy to access and combine the scores generated by the different modalities. Consequently, integration of information at the matching score level is the most common approach in multiple modal biometric systems.

Consolidating the evidence obtained from multiple classifiers, one can use schemes like the sum rule, product rule, max rule, min rule, and median rule. Meanwhile, the scores from each modality can be weighted by selecting the values to reflect the reliability and discrimination ability of each modality, which can be adaptive or fixed [51]. The important issue is the weight selection in this fusion level. Therefore, weighted

summations by Golden Ratio method (GR) have been proposed in this dissertation. In this section, the basic idea of golden section search is briefly reviewed, and golden ratio method (GR) is introduced for the score fusion, especially for an AV system; later we will present the architecture of the score fusion for this system.

10.2.1 Golden Ratio Basics

It is possible to utilize previous information to locate succeeding experiments by applying for a sequential search. It leads to a great reduction in the final interval of uncertainty for the same number of experiments. One of the most efficient sequential search plans is called Fibonacci search [39]. This method requires that the number of experiments be specified in advance, which may be inconvenient in most cases. But golden section search is almost as efficient as Fibonacci search, and the benefit is it does not require that the number of experiments must be specified in advance.

In mathematics, two quantities are in the golden ratio if the ratio between the sum of those quantities and the larger one is the same as the ratio between the larger one and the smaller one. The golden ratio is approximately 1.6180339887. Other names frequently used for or closely related to the golden ratio are golden section, golden mean, golden number, and the Greek letter phi (φ) [39].

In general speaking, golden section search is a technique for finding the minimum or maximum of a function. It can successively narrow down the range of values within which the max/min is known to exist.

Fig. 10.2 illustrates this method to find a minimum and the search steps are listed as below:

1) Start with interval (a, b, c)

2) Divide the large part of the interval in the ratio 1 to φ to get *d*

3) Find function result *F(d)*

4) If *F(d)* > *F(b)* new interval is (*a*, *b*, *d*), otherwise new interval is (*b*, *d*, *c*)

5) Find the minimum sufficiently accurately? Yes, then stop, otherwise, go to step 2).

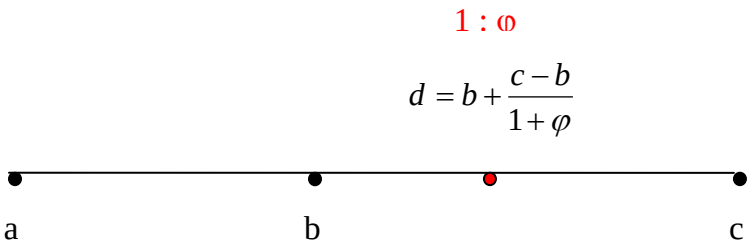


Figure10.2 Golden section search

The Golden section search does not require knowing about the derivative of function. If the derivative of function is available, it will lead to faster convergence of search because the derivative helps predict the best direction of choosing the new point ***d***, leading to faster convergence [39].

10.2.2 Proposed golden ratio method

In score fusion, the scores of modality-specific classifiers are combined and the final score is used to make a decision. Typically the output of modality-specific classifiers is lineally combined through a set of fusion weights. Given ***N*** scores $\boldsymbol{S_N}$ from ***N*** biometrics, GR method can achieve the final score ***F*** by the following equation,

$$F = \sum_{i=1}^{N-1} \alpha_i S_i + (1 - \sum_{i=1}^{N-1} \alpha_i) S_N \tag{10.1}$$

where $\{\alpha_i\}$ are a set of fusion weights, and $\alpha_i \in [0, 1]$.

Specifically to a bi-modal system like audio and visual system, the following can represent the above equation for GR1 method:

$$F = \alpha * S_F + (1-\alpha) * S_v \tag{10.2}$$

where $\alpha \in [0, 1]$, $\boldsymbol{S_F}$ and $\boldsymbol{S_v}$ are the scores for visual and audio information, respectively.

The golden section search method can help to find the minimum/maximum value by narrowing down the range of values. It can be applied in our AV system to obtain the weight $\boldsymbol{\alpha}$ between the audio's and visual scores in GR method, then finally get the fused score value $\boldsymbol{F}$ to recognize persons under test.

To more than two modalities in multiple modal biometric systems, it is difficult to obtain the set of fusion weights $\boldsymbol{\alpha_i}$ by GR method because of more unknown variables. But it is very convenient and easy to search the weight $\boldsymbol{\alpha}$ for two modalities.

In any multiple modal biometric systems, feature extraction techniques are essential before obtaining the score of each biometric modality. In the case of AV system, MFCC and PGE algorithms are employed to achieve the feature vectors of audio and visual biometric traits respectively. And PNN has been used to get the matching scores of each modality for the subject under test.

10.3 Case Study: Audio-visual Biometric System

10.3.1 AV feature extraction

This section describes a case study for the proposed golden ration fusion methods. A virtual database is used to test the algorithm, which is composed of static people face images and speech clips of 40 subjects.

Briefly speaking, the database used in this section includes audio (speech) part and visual (face) part. A virtual subject was constructed by assigning a speech subject to a

face subject. The database setup will be the same with the one in previous chapters, and two data sessions will be employed in the following experiments. For the details of database session 1 and 2, please refer to the previous chapters.

No matter which level fusion the multi-modal biometric system applies, feature extraction module of each individual modality is one of the most essential steps, because the performance of systems strongly relies on the accurate extraction of biometric features from original biometric sources.

As a case study, an Audio-visual (AV) system composed of static face images and text-independent speeches is investigated in this research. In the AV system under investigation, visual features are extracted by the Pyramidal Gabor wavelet with the Eigenface (PGE) algorithm [11] and audio features are extracted by the Mel Frequency Cepstrum Coefficients (MFCCs) algorithm [3]. For some information about the feature extraction, please see previous chapters.

10.3.2 Experiment

In order to compare the performances from the proposed method and the two related single modal methods under the PNN framework, two experiments were conducted. In experiment 1, it was chosen that, for each virtual subject, the length of the audio signals was 25 seconds for training and 12.5 seconds for testing; and in experiment 2, 20 seconds for training and 10 seconds for testing. In both of the experiments, six face images of each subject were employed for training and four remaining face images for testing. In addition, the codebook size for VQ was initialized as 128. Furthermore, the number of MFCC coefficients was set to 12.

Table 10.1 compares the results from the two related single modal methods. With the setup described above, if only the audio-based features were used for human identification, implemented with a similar PNN structure, the recognition rates were only 47.5% and 43.5%, respectively; and the recognition rate was improved to 96% by using only the visual-based features with 239 eigenvectors. These results indicate that PGE was suitable for recognizing purposes. The Gabor wavelet representation facilitates recognition without correspondence in PGE algorithm, because it captures the local structure corresponding to spatial frequency, spatial localization, and orientation selectivity. As a result, the Gabor wavelet representation of face images is robust to deal with the variations caused by illumination condition, viewing direction, poses, facial expression changes and disguises.

Also, shown in Table 10.1 were the experimental results which suggested that the recognition rate was not accepted as of the single audio modal applied. This is expected, as the performance of speaker recognition heavily relies on the clearness of audio signals.

Methods	Recognition rate for best performance length of training audio (s) / length of testing audio (s)	
	25s / 12.5s	20s / 10s
Audio-based modal	47.5%	43.5%
Visual-based modal	96%	96%

Table 10.1 Recognition rates of single modal system

Table 10.2 shown the testing results with 19 and 239 eigenvectors used for visual scores, respectively, and indicated that the visual part gained more weight than the audio part in GR algorithm, because it is more reliable than audio signal that includes some background noises. It is a reasonable and expected result. Also, with the incensement of

the number of eigenvectors, the test result is much better. Meanwhile, from Table 10.1 and 10.2, the best performance of AV systems at score level fusion is better than single modal involved in the test when using 239 eigenvectors.

Methods		Rates	Value of α_F or i
GR	19 eigenvectors	87.5%	0.9017
	239 eigenvectors	100%	0.9868

Table 10.2 Performance at score fusion level

10.4 Conclusion

This chapter introduces GR algorithms to combine the matching scores of multiple modalities involved in a biometric system. GR method is developed to obtain the biometric contribution of different modalities in a system. In another word, it tries to find the right weights of sources in order to pursue a better recognition rate.

Meanwhile, GR is very convenient to be used in bi-modal systems instead of more than two modality systems. As a case study, the method is performed in an audio-visual system, which consists of static visual images and the relevant text-independent audio clips. And in this constructed AV system, visual information takes more advantages than audio information because the heavy background noise affects the results of audio signals, which makes speaker recognition hard to recognize the subject under test. The weights obtained by GR have indicated the reliability of visual information, which is an expected result. When comparing with the single modal systems, one can discover that the fusion methods used in AV bi-modal system perform better than any single modal system without a fusion strategy.

Comparing with the ones in literature, the proposed method is much easier, faster, and simpler when implementing. Of course, such algorithm will not take much computation time and data storage. Also, due to the maturity of golden ration method, GR has a strong theoretical basis. Furthermore, it can be utilized other than AV bi-modal systems.

11 CONCLUSION

Biometrics is one of science's truly cutting-edge technologies. Such a technology refers to the methods for uniquely recognizing humans based upon intrinsic physical or behavioral traits. In 2001, *MIT Technology Review* named biometrics as one of the "top ten emerging technologies that will change the world". Example deployments within the United States Government include the FBI's Integrated Automated Fingerprint Identification System, the US-VISIT program, the Transportation Workers Identification Credentials program and so on.

This dissertation has proposed and discussed several novel approaches for biometric recognition, including face-only and voice-only person recognition methods and multiple modal biometric fusion methods, especially in feature and score levels. The author has developed an algorithm for face recognition by introducing Pyramidal Gabor Wavelets with one dimensional filter masks and Eigenface. Such method "considerably reduces the amount of processing power that face recognition requires without compromising accuracy, even with low-resolution images."

The author has also developed several other new algorithms about biometric fusion for multiple modal biometrics by performing probabilistic analysis, genetic method, neural network, simulate annealing technique, etc. These methods include 1) feature fusion by synchronization of feature streams, 2) fusion by Link Matrix algorithm, 3) fusion by Genetic algorithm, 4) fusion by Simulated Annealing, 5) fusion by Golden

Ratio. Some of the above algorithms can be extended to other fusion levels like sensor level.

The methods developed for biometric fusion in this dissertation are much more robust and reliable than face-only and voice-only biometrics.

The future work is to employ the above research work to other databases, and apply for facial expression analysis and other smart environment design, which employ audio-visual multiple biometric traits to recognize people's needs.

12 APPENDIX

A. The steps of Link Matrix *B*:

1) Randomly generate a matrix *B* that satisfies (7.4) (or (7.6));
2) Compute the objective function *C* with the matrix *B* using (7.5) (or (7.7));
3) Save both matrix *B* and result *C*, and set *B* as B_{best} and *C* as C_{best}, regarding B_{best} as the current solution;
4) Randomly generate another matrix *B* that satisfies (7.4) (or (7.6));
5) Evaluate the objective function *C* using (7.5) (or (7.7)) with the new matrix *B* obtained in Step 4):
   a) If *C* is better than C_{best}, replace B_{best} with the new *B* and update C_{best}.
   b) Otherwise, just ignore the new solution.
6) Iterate the steps 4) and 5) till either the error *C* is below a preset tolerance or the maximum number of iterations is reached.

B. Some programs:

1). Training step of PGE:

```
function [EN, averageFace, anyMean, anyStd, projDifSet ] = ...
  faceTrain (numTrainingImg, xd, yd)

faceSet = [];
averageFace = [];
figure(1);
for i = 1:numTrainingImg
   str = strcat( 'G:\Lin\dataAttFace\training5end\',int2str(i), '.jpg');
   eval('img = imread(str);');
   subplot( ceil(sqrt(numTrainingImg)),ceil(sqrt(numTrainingImg)),i )
   im = double(rgb2gray(img));
   imshow(im, [min(min(im)) max(max(im))]);

   % Call Gabor Decomposition
   [l, lpr, hpr] = gaDec(im, 4, 1, 1, 2);
   face1=[];
   for ii=1:4
      for jj=1:4
         rel{ii}(:,:,jj) = l{ii}(:,:,jj);
         iml{ii}(:,:,jj) = l{ii}(:,:,jj+4);
         num{ii}(:,:,jj) = rel{ii}(:,:,jj) + i*iml{ii}(:,:,jj);
         anum{ii}(:,:,jj) = abs(num{ii}(:,:,jj));
         tt = anum{ii}(:,:,jj);
         tt1 = tt';
         imcol = tt1(:);
         face1=[face1; imcol];
      end
   end

   % Get mean and variation for each trained face
   m1(i) = mean(face1);
   std1(i) = mean(face1);
   faceSet = [faceSet face1];  % faceSet
end
xlabel('Training Face Sets','fontsize',10)
anyMean = mean(m1);
anyStd = std(std1);

for i = 1: numTrainingImg
   temp = faceSet(:,i);
   faceSet(:,i) = (temp - mean(temp))*anyStd/std(temp) + anyMean; % end
```

```
averageFace = mean(faceSet,2);   %

for i = 1: numTrainingImg
   difSet (:,i) = faceSet(:,i) - averageFace;
end
R = difSet'* difSet;
[vect,valu] = eig(R
colVect = size(vect,2);
vec = [];  val = [];
for i = 1: colVect
   if (valu(i,i) > 1e-5)
      vec = [vec vect(:,i)];
      val = [val valu(i,i)];
   end
end
numVal = size(val,2);

[temp, index] = sort(val);
for j = 1:numVal
   val(j) = temp(numVal - j + 1); % vecUpdated
   vecUpdated(:,numVal-index(j)+1) = vec (:,j);
end

% Normalize eigenVector vecUpdated
for i = 1: size(vecUpdated,2)
   temp = vecUpdated(:,i);
   vec(:,i) = vecUpdated(:,i)./(sqrt(sum(temp.^2)));  %
end
E = difSet*vec;
for i = 1: size(val,2)
   for j = 1: size(val,2)
      if i == j
         lamda(i,j) = 1/sqrt(val(i));
      else
         lamda(i,j) = 0;
      end
   end
end
EN = E*lamda;
projDifSet = EN'*difSet;
```

2). Test step of PGE:

```
function [mid, mad, dis, proj] = faceRec2009(numTestingImg, ...
      EN, averageFace, anyMean, anyStd, projDifSet)
mid = [];
mad = [];

% Input and draw the test image
for k = 1: numTestingImg
      str = strcat( 'G:\Lin\dataAttFace\testing5\',int2str(k), '.jpg');
      eval('img = imread(str);');
      testImg = rgb2gray(img);
      figure (6);
      subplot( ceil(sqrt(numTestingImg)), ceil(sqrt(numTestingImg)),k )
      imshow(testImg, [ min(min(testImg)) max(max(testImg))]); colormap('gray');

      im = double(testImg);
      [l, lprt, hprt] = gabDec(im, 4, 1, 1, 2);
      % Compute difference image and projection to eigenspace

      % Get every face's Gabor vectors imcol by raster scanning
      face1=[];
      for ii=1:4
      for jj=1:4
         rel{ii}(:,:,jj) = l{ii}(:,:,jj);
         iml{ii}(:,:,jj) = l{ii}(:,:,jj+4);
         num{ii}(:,:,jj) = rel{ii}(:,:,jj) + i*iml{ii}(:,:,jj);
         anum{ii}(:,:,jj) = abs(num{ii}(:,:,jj));
         tt = anum{ii}(:,:,jj);
         tt1 = tt';
         imcol = tt1(☺;
         face1=[face1; imcol];
      end
      end

      temp = face1;
      testNorm = (temp – mean(temp))*anyStd/std(temp) + anyMean;
      testDif = testNorm – averageFace;% Compute the difference
      projTest = EN'*testDif;% projection of the test image on eigenspace
      proj(:,k) = projTest;

   % Find Euclidean distance and find results
      …….
```

3). Codebook creation of speaker recognition:

```
function [training_features,testing_features]=sp(num_train,num_test)
   codeBookSize=2^7;
   plotOpt=0;
   No_of_Gaussians = 2;
   training_data = [];
   testing_data = [];
   training_features = [];
   testing_features = [];
   mu_train = [];
   sigma_train = [];
   c_train = [];
   againstModel = [];
   Fs=8000;   %or obtain this from wavread

   num_train = input (' Please input the number of training data: ');
   for i = 1:num_train
      str = strcat ('E:\dataPublicVoice\', int2str(i), '_train.wav');
      eval ( 'training_data(:,i) = wavread(str, [1000 201000]);');
   end
   disp(' Completed reading training data (Press any key to continue)');
   pause;
   num_test = input (' Please input the number of testing data: ');
   for i = 1:num_test
      k = input (' Which speech data will you want to test? (1~12) ');
      str = strcat ('E:\dataPublicVoice\', int2str(k), '_test.wav');
      test_order(i) = k;
      eval ( 'testing_data(:, i) = wavread(str, 100000);');
   end
   disp(' Completed reading test data (Press any key to continue)');
   pause;

   tar = ones(1,codeBookSize);
   neu = [];
   temp1 = [];
   target = [];
   for i = 1: num_train
     train_Fea= melcepst (training_data(:,i), Fs, 'M', 30);

     codebook = vqLBG_bb(train_Fea, codeBookSize, plotOpt);
     fprintf ('Completed VQ for the codebook of training speaker %d \n', i);
     codeBook = normalization(codebook);
     training_features (:,:,i)= codeBook(:,:);
     neu = [neu codeBook'];

     % Obtain the targets and neurons vectors to construct the pnn
```

```
    target = [target i*tar];

end
disp('Completed Feature extraction, VQ for the training data (Press any key to
continue)');
pause;


for i = 1: num_test
  test_Fea= melcepst (testing_data(:,i), Fs, 'M', 30);
  codebook = vqLBG_bb(test_Fea, codeBookSize, plotOpt);
  fprintf ('Completed VQ for the codebook of testing speaker %d \n', i); codeBook =
normalization(codebook);   testing_features (:,:,i)= codeBook(:,:);

end
disp('Completed feature extraction, VQ for the testing data (Press any key to
continue)');
pause;

net = newpnn( neu, ind2vec(target), 0.1 );
for i = 1: num_test
   test1(:,i) = vec2ind(sim( net, testing_features(:,:,i)'));
end


for i = 1:num_test
   index = test1(:,i);
   classInd = zeros(num_test, 128);
   for j=1: 128
      classInd(index(j,:),j) = 1;
   end

   tt2=sum(classInd,2);
   for j=1:num_train
      if max(tt2) == tt2(j,:)
         ind = j;
      end
   end
   cla(i) = ind;
end
```

4). LS for AV feature fusion:

```
% This program is for LS method to classify AV features.
% Before using this program, u have to load the saved data files
load …..
ir1train=floor(128/numPatternTrain);
ir2train = rem(128, numPatternTrain);
ir1test=floor(128/(10-numPatternTrain));
ir2test=rem(128, (10-numPatternTrain));
dim= No_of_Mfcc + numEigen;

for i = 1: 40
      for k = 1: numPatternTrain
      for j =1: ir1train
         trainface(j+(k-1)*ir1train, :, i) = CodesProjDifSet(:,k+(i-
1)*numPatternTrain);
      end
   end
   if ir2train ~= 0
      for k = 1: ir2train
         trainface(128-k+1,:, i) = CodesProjDifSet(:,1+(i-
1)*numPatternTrain);
      end
   end

   for k = 1: 10-numPatternTrain
      for j = 1: ir1test
         testface(j+(k-1)*ir1test, :, i) = CodesProj(:,k+(i-1)*(10-
numPatternTrain));
      end
   end
   if ir2test ~= 0
      for k = 1: ir2test
         testface(128-k+1,:, i) = CodesProj(:,1+(i-1)*(10-numPatternTrain));
      end
   end

   for k=1:128
      trainVector(k,:,i) = [training_features(k,:,i) trainface(k,:,i)];
      testVector(k,:,i) = [testing_features(k,:,i) testface(k,:,i)];
   end
end

LS=zeros(40,40);
classID=[];
```

```
for k=1:40
   for m=1:40
      for i=1:128
         for j=1:size(trainVector,2)
            LS(k,m) = LS(k,m)+(testVector(i,j,k)-trainVector(i,j,m))^2;
         end
      end
   end
   for m=1:40
      if LS(k,m)== min(LS(k,:))
         classID(k)=m;
      end
   end
end
```

5). Random search method for AV fusion:

```
load inputPattern1;
load inputPattern2;

nsubj = input('Num of training subjects in the database: ');
ntest = input('Num of testing subjects in the database: ');
numOne = input('Num of ones in a row: ');
numOneTe = input('num of the 1s for test database: ');

nfp = size(face,2);
nvp = size(voice, 2);
nfpTe = size(faceTest,2);
nvpTe = size(voiceTest, 2);

xdir = nfp/nsubj;
ydir = nvp/nsubj;
xdirTe = nfpTe/ntest;
ydirTe = nvpTe/ntest;

xy0 = randomSelect(numOne, ydir, xdir);
temp = sum(xy0);
% Initialize the matrix which satisfy the condition
i = 1;
while i<=xdir,
   if temp(i)== 0,
      clear temp;
      xy0 = randomSelect(numOne, ydir, xdir);
      temp = sum(xy0);
      i = 1;
   else
      i = i+1;
   end
end

xyTe = randomSelect(numOneTe, ydirTe, xdirTe); % Initialize the matrix
i = 1;
while i<=xdirTe,
   if temp(i)== 0,
      clear temp;
      xyTe = randomSelect(numOneTe, ydirTe, xdirTe);
      temp = sum(xyTe);
      i = 1;
   else
      i = i+1;
   end
```

```
end


%For initialized xy0, one can get the recog results
[avTr1,T1]=fuseFun(xy0,ydir,xdir,nsubj,numOne,voice,face);
[avTe1,T3]=fuseFun(xyTe,ydirTe,xdirTe,ntest,numOneTe,voiceTest,faceTest);

Target1 = ind2vec(T1);
net = newpnn(avTr1,Target1);
Y = sim(net,avTe1);
index1 = vec2ind(Y)
ind=[];
for k = 1:ntest,
   s=zeros(ntest, nsubj);
   for i = 1: nsubj,
      for j = 1: ydir,
         if index1((k-1)*ydir+j) == i
            s(k,i) = s(k,i) + 1;
         end
      end
   end

   for i = 1:nsubj,
      if max(s(k,:))==s(k,i)
         ind(k) = i;
      end
   end
end

disp('Index for the ID of all the test pattern');
ind %index for the ID of all the test patterns

numError = 0.0;
for i =1:ntest,
   if(ind(i) ~=i) %it is special case when testing order is the order of natural number
      numError = numError + 1;
   end
end
rate = numError/ntest;
```

6). Another sample for AV fusion:

```
load my6face25s12mcc20eig;
nsubj = input('Num of training subjects in the database: ');
ntest = input('Num of testing subjects in the database: ');
testOrder =[];
face =[];
voice =[];
faceTest =[];
voiceTest =[];

for i =1:ntest,
   temp = input('please input testing order: ');
   testOrder = [testOrder temp];
end

face = CodesProjDifSet;
voice = neu;
for i = 1: numTest,
   for j = 1: 10-numPatternTrain,
      faceTest(:,j,i) = CodesProj(:,j+(i-1)*(10-numPatternTrain));
   end
   voiceTest(:,:,i) = testing_features(:,:,i)';
end

numOne = 1;
xdir = numPatternTrain; %xdir stands for the face pattern number
ydir = 128; %ydir stands for the voice pattern number
xdirTe = 10-numPatternTrain;
ydirTe = ydir;
BTr =[]; %Set up for the matrix, which will be used to fuse AVTraing
BTe =[]; %Set up for the matrix, which will be used to fuse AVTesting

for nite = 1: 50, %100 is maximum interation num
   xy0= randomSelect(numOne, ydir, xdir);
   tempx = sum(xy0,1);
   tempy = sum(xy0,2);
   i = 1;
   j = 1;
   while i<=xdir && j<=ydir
      if tempx(i)== 0 || tempy(j)==0
         clear tempx tempy;
         xy0= randomSelect(numOne, ydir, xdir);
         tempx = sum(xy0,1);
         tempy = sum(xy0,2);
         i = 1;
```

```
        j = 1;
    else
        i = i + 1;
        j = j + 1;
    end
end


xyTe = randomSelect(numOne, ydirTe, xdirTe);
i = 1;
j = 1;
tempx = sum(xyTe,1);
tempy = sum(xyTe,2);
while i<=xdirTe && j<=ydirTe
    if tempx(i)== 0 || tempy(j) ==0
        clear tempx tempy;
        xyTe = randomSelect(numOne, ydirTe, xdirTe);
        tempx = sum(xyTe,1);
        tempy = sum(xyTe,2);
        i = 1;
        j = 1;
    else
        i = i+1;
        j = j+1;
    end
end
[avTr1,T1]=fuseFun(xy0,ydir,xdir,nsubj,numOne, voice,face);
[sig, mea] = stdVariance(face');
net = newpnn(avTr1,ind2vec(T1),sig);

test1 = [];
for i = 1: ntest
    avTe1=fuseAVtest(xyTe,ydirTe,xdirTe,voiceTest(:,:,i),faceTest(:,:,i));
    test1(:,i) = vec2ind(sim(net, avTe1));
end
save myAVtestResult test1 ntest nsubj testOrder xyTe xy0 nite numOne ...
    BTr BTe xdir ydir xdirTe ydirTe face voice voiceTest faceTest;
clear all;

load myAVtestResult;

temp = size(test1(:,1));
index = [];
tt2=[];
cla = [];
```

```
    for i = 1:ntest
        index = test1(:,i);
        classInd = zeros(nsubj, temp(1,1));
        for j=1: temp
            classInd(index(j),j) = 1;
        end
        tt2=sum(classInd,2);
        for j=1:nsubj
            if max(tt2) == tt2(j,:)
                ind = j;
            end
        end
        cla(i) = ind;
    end

    numError = 0.0;
    for i =1:ntest,
        if(cla(i) ~= testOrder(i))
            numError = numError + 1;
        end
    end
    rate(nite) = numError/ntest;
    q2(nite)= sum(numOne)/(xdir*ydir);
    obj(nite) = rate(nite) + 0.5*q2(nite);

    BTe(:,:,nite)=xyTe;
    BTr (:,:,nite) = xy0;
end
```

7). Sample program for AV fusion:

```
% Demo for GA algorithm with PNN classification

load voiceVQResult; load visualNoDownResult4AV;
 neu_fsp = [ neu; faceFeaTr];
Vtr = []; Vte = []; Atr = []; Ate = [];

for i = 1: 40
for j = 1: 6 %
       Vtr(:, j, i) = CodesProjDifSet(:, (i-1)*6+j);
   end
   for j = 1:4
      Vte(:, j, i) = CodesProj(:, (i-1)*4 +j);
   end
   Atr(:,:,i) = training_features(:,:,i)';
   Ate(:,:,i) = testing_features(:,:,i)';
end

AVte = [];
Ate_temp = [];
Vte_temp = [];
for i = 1:40
   Ate_temp(:,i) = reshape(Ate(:,:,i)', [], 1);
      for j = 1: 4        ]
       Vte_temp(:,i) = [Vte(:,j,i); Vte(:,j,i); Vte(:,j,i); Vte(:,j,i); Vte(:,j,i); Vte(:,j,i)];
      AVte(:,(i-1)*4+j) = [Ate_temp(:,i); Vte_temp(:,i)];
   end
end
clear Vtr_temp Atr_temp;
temp = ones(1,4);
testOrder = [];

for i = 1:40
   testOrder = [testOrder i*temp];
end

options = gaoptimset('PopInitRange',[20;24],'Generations',1000, 'PopulationSize',...
   80, 'MutationFcn',@mutationuniform,'SelectionFcn',@selectionroulette,...
   'CrossoverFcn',@crossovertwopoint );
[X,FVAL,REASON] = ga(@(X)fitnessfunc(X, Vtr, Atr, AVte, testOrder), 6,options);
[Y,F2,REASON] = ga(@(Y)fitnessfuncLS(Y, Vtr, Atr, AVte, testOrder), 6,options);
```

8). Sample program of AV fusion:% Demo for SA algorithm with PNN classification

```
load voiceVQResult; load visualNoDownResult4AV;
neu_fsp = [ neu; faceFeaTr];
Vtr = []; Vte = []; Atr = []; Ate = [];

for i = 1: 40
   for j = 1: 6
      Vtr(:, j, i) = CodesProjDifSet(:, (i-1)*6+j);
   end
      for j = 1:4
      Vte(:, j, i) = CodesProj(:, (i-1)*4 +j);
   end
   Atr(:,:,i) = training_features(:,:,i)';
   Ate(:,:,i) = testing_features(:,:,i)';
end

AVte = []; Ate_temp = []; Vte_temp = [];
for i = 1:40    Ate_temp(:,i) = reshape(Ate(:,:,i)', [], 1);
   for j = 1: 4        Vte_temp(:,i) = [Vte(:,j,i); Vte(:,j,i); Vte(:,j,i); Vte(:,j,i); Vte(:,j,i);
Vte(:,j,i)];
      AVte(:,(i-1)*4+j) = [Ate_temp(:,i); Vte_temp(:,i)];
   end
end
clear Vtr_temp Atr_temp;
temp = ones(1,4);
testOrder = [];

for i = 1:40
   testOrder = [testOrder i*temp];
end

  x0 = zeros (1, 6);  lb = ones (1, 6); ub = 24.00 * ones (1, 6);
  options = saoptimset('AnnealingFcn', @annealingboltz, 'InitialTemperature', 1000,...
     'TemperatureFcn',@temperatureboltz,'MaxIter',100, ...
     'PlotFcns',{@saplotbestx,@saplotbestf,@saplotx,@saplotf});
[X,FVAL] = simulannealbnd(@(X)fitnessfunc(X, Vtr, Atr, AVte, testOrder), x0, lb,ub,
options );
[Y,F2,REASON] = simulannealbnd(@(Y)fitnessfuncLS(Y, Vtr, Atr, AVte, testOrder),
6,options);
```

9). Golden section for AV fusion:

```
function [alist, blist, err1, err2] = golden(a0, b0, sc1, sc2, numPatternTrain, numTrain)

%Initialize the iteration times N and golden ratio r
N = 40;
r = (sqrt(5)-1)/2;
er1 = 0;
er2 = 0;
err1 = zeros(N,1);
err2 = zeros(N,1);
ff1 = []; % 40 x 40 matrix
ff2 = []; % 40 x 40 matrix
alist = zeros(N,1);
blist = zeros(N,1);
a = a0;
b = b0;
s = a + (1-r)*(b-a);
t = b - (1-r)*(b-a);
ff1 = s.*sc1 + (1-s).*sc2; % ff1 and ff2 will be a matrix 40 x 40
ff2 = t.*sc1 + (1-t).*sc2;

for i = 1: numTrain,
   if max(ff1(:, i))~= ff1(i,i)
      er1 = er1+1;
   end
   if max(ff2(:,i)) ~= ff2(i,i)
      er2 = er2+1;
   end
end
f1 = er1/numTrain;
f2 = er2/numTrain;
e10= f1;
e20= f2;

for n = 1:N
   if f1 < f2
      b = t;
      t = s;
      s = a+(1-r)*(b-a);
      f2 = f1;
      %f1 = f(s);
      ff1 = s.*sc1 + (1-s).*sc2;
      er1 = 0;
      for i = 1: numTrain,
         if max(ff1(:,i))~= ff1(i,i)
```

```
            er1 = er1+1;
        end
    end
    f1 = er1/numTrain;
    err1(n) = f1;
else
    a = s;
    s = t;
    t = b-(1-r)*(b-a);
    f1 = f2;
    ff2 = t.*sc1 + (1-t).*sc2;
    er2 = 0;
    for i = 1: numTrain,
        if max(ff2(:,i)) ~= ff2(i,i)
            er2 = er2+1;
        end
    end
    f2 = er2/numTrain;
    err2(n) = f2;
end
alist(n) = a;
blist(n) = b;
end
disp('     a       b       b-a   ')
disp(' ')
alist = [a0;alist];
   blist = [b0; blist];
   err1 = [e10; err1];
  err2 = [e20; err2];
   [alist, blist, err1, err2, blist-alist]
```

10). Another sample program of Golden power method for AV fusion:

```
% Function for golden cut/ golden section
% use f function by:
%          score = faceScore.^i/(faceScore.^i+voiceScore.^i)*faceScore
%              + voiceScore.^i/(faceScore.^i +voiceScore.^i)*voiceScore

function [alist, blist, err1, err2] = goldenPower(a0, b0, sc1, sc2, numPatternTrain,
numTrain)
N = 40;
r = (sqrt(5)-1)/2;
er1 = 0;
er2 = 0;
err1 = zeros(N,1);
err2 = zeros(N,1);
ff1 = []; % 40 x 40 matrix
ff2 = []; % 40 x 40 matrix
alist = zeros(N,1);
blist = zeros(N,1);
a = a0;
b = b0;
s = a + (1-r)*(b-a);
t = b - (1-r)*(b-a);
ff1 = ((sc1.^s)./(sc1.^s+sc2.^s)).*sc1 + ((sc2.^s)./(sc1.^s+sc2.^s)).*sc2;
ff2 = ((sc1.^t)./(sc1.^t+sc2.^t)).*sc1 + ((sc2.^t)./(sc1.^t+sc2.^t)).*sc2;

for i = 1: numTrain,
   if max(ff1(:, i))~= ff1(i,i)
      er1 = er1+1;
   end
   if max(ff2(:,i)) ~= ff2(i,i)
      er2 = er2+1;
   end
end
f1 = er1/numTrain;
f2 = er2/numTrain;
e10= f1;
e20= f2;

for n = 1:N
   if f1 < f2
      b = t;
      t = s;
      s = a+(1-r)*(b-a);
      f2 = f1;
      ff1 = ((sc1.^s)./(sc1.^s+sc2.^s)).*sc1 + ((sc2.^s)./(sc1.^s+sc2.^s)).*sc2;
```

```
        er1 = 0;
        for i = 1: numTrain,
            if max(ff1(:,i))~= ff1(i,i)
                er1 = er1+1;
            end
        end
        f1 = er1/numTrain;
        err1(n) = f1;
    else
        a = s;
        s = t;
        t = b-(1-r)*(b-a);
        f1 = f2;
        ff2 = ((sc1.^t)./(sc1.^t+sc2.^t)).*sc1 + ((sc2.^t)./(sc1.^t+sc2.^t)).*sc2;
        er2 = 0;
        for i = 1: numTrain,
            if max(ff2(:,i)) ~= ff2(i,i)
                er2 = er2+1;
            end
        end
        f2 = er2/numTrain;
        err2(n) = f2;
    end
    alist(n) = a;
    blist(n) = b;
end
disp('     a       b       b-a   ')
disp(' ')
alist = [a0;alist];
    blist = [b0; blist];
    err1 = [e10; err1];
   err2 = [e20; err2];
    [alist, blist, err1, err2, blist-alist]
```

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