Università degli Studi di Cagliari

Facoltà di Ingegneria

Dipartimento di Ingegneria Elettrica ed Elettronica

STRUCTURAL AND GRAPH-BASED METHODS FOR AUTOMATIC FINGERPRINT CLASSIFICATION

PhD Thesis of: Alessandra Serrau

Supervisor: Prof. Fabio Roli

Dottorato di Ricerca in Ingegneria Elettronica e Informatica

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Preface

The topic of the present Ph.D. thesis is the investigation of the role of multiple classifier system for fingerprint recognition. We mean, with the term *recognition*, two main applications:

1. *Biometric identification:* the automatic association of a certain identity to the person that submit his/her fingerprint

2. *Biometric verification:* the automatic verification that the actual identity of the person corresponds to the claimed one, by comparing his/her fingerprint with the one stored in the system data base and associated to the claimed identity

According to such categorisation, it is a question of:

1. the identity of each person

2. the users which are allowed/not allowed to access to the system

Technologies of such biometric are very promising and it can have a wider spectrum of applications than others. In this work, fingerprint biometric has been represented with different approaches, wich require different algorithms for recognition. Then, we combined the outputs of such algorithms by designing various multiple classifiers systems in order to:

- increase the performance with respect to that of the best individual classifier

- point out the *complementarity* of different classifiers. The term *complementarity* could be intuitively explained as follows: if two classifiers correctly classify patterns localised on different sudsets of the features space, their "fusion" could exploit such ability. Therefore, it could be possible to design a multiple classifiers system able to correctly classify all patterns in all features space subsets. In our opinion, this aspect is not yet sufficiently investigated in the literature for automatic biometric systems

The Ph.D. thesis is organised as follows.

Chapter 1 is aimed to present the principal concepts behind biometrics: what they are, the structure of a biometric recognition system, the main performance evaluation parameters.

Chapter 2 describes the main approaches prensent in the state of the art, with particular attention to statistical and structural methods.

Chapter 3 introduces the innovative proposed methods. All our methods are structural, that is, they classify pattern described by structural data such as graphs or threes. In particular we evaluate the performance of recursive neural networks and structural K nearest neighbors approach as individual classifiers.

Chapter 4 investigates the advantages of fusing approaches described in chapter 3, firstly themselves, then with the main statistical approach, the so called *FingerCode*. Moreover, approaches to design ensembles of statistical classifiers are described in order to evaluate which of these could be also used

for structural classifiers.

Chapter 5 deeply shows the experimental results of all investigated methods: individual classifiers, their diverse combinations and ensembles of them.

The book closes with some considerations on the present utility and the future potentialities of graph-based methods for fingerprint classification.

Alessandra Serrau

Chapter 1

Introduction to Biometrics

Personal identification is since the earliest times a felt issue and, at the same time, doesn't have a simple solution. Nowadays, it is becoming a very important social aspect and its importance enormously grew because of a major need of security, such as dangerous people recognition into banks, airports and other public environment in which terrorists or other criminals could operate.

A traditional authentication system is based on something that the person know, i.e. a password, or something that the person has i.e. a smart card. Nevertheless password and smart card may be lost, stole, forgot or forged.

On the other hand, an approach of biometric authentication is not based on knowledge or possession but on body characteristics (finger, eyes, face) and ways to do (talk, write); these characteristics could be considered unambiguous. Therefore, biometrics are the physiological and behavioural human characteristics and so offer protection to the user from the identity theft.

The biometric systems, since few years ago used only in specific environments with high security level, now are much required in many sectors.

Moreover, the drastic costs reduction of these systems in the last years, makes more interesting biometric tecnologies for business too.

1.1 Biometrics and properties

The *identification* process consists in associating a certain identity to a person. The identification can be:

- *Positive*: the person to be identified declares her/his identity. In this case, the identification process must verify that claimed identity and person correspond. This kind of identification is often called *identification one to one.*
- *Negative*: the identification process requires a comparison between the person to be identified and other persons in a data base, in order to find his/her identity. This kind of identification is often called *identification one to many.*

A behavioural or physiological characteristic is a biometric if it holds the following properties:

- *Universality*: it can be found in all people
- *Uniqueness*: it is unique from person to person
- *Permanence*: it does not change over the time, during the live
- *Collectability*: it is possible to capture it quantitatively

Besides, for using a biometric in real applications, it must have the following properties:

- *Performance*: the biometric allows to distinguish the persons with high degree of accuracy
- *Acceptability*: the biometric must be accepted by the users
- *Circumvention*: the violability degree of the system must be very low

1.2 Main biometrics

In this section we briefly review the main biometrics. Figure 1.1 shows the most important biometrics. For details, see [Jain 1999].

Fingerprint

They are the most famous biometric. A fingerprint pattern is described by the epidermic ridges and valleys. In this thesys we'll deepen such biometric.

Face

The face is the oldest biometric for personal recognition because it is the most natural characteristic to recognise each other [Wechsler 1997]. Advantages are non intrusion and person non collaboration. Drawbacks are difficulty in the algorithms that are strongly dipendent of environmental variability such as lighting conditions and expression and pose in front of a camera.

Iris

The iris structure is unique for each individual. It can be acquired through a specialized camera at a certain distance from the subject. Thus, the iris

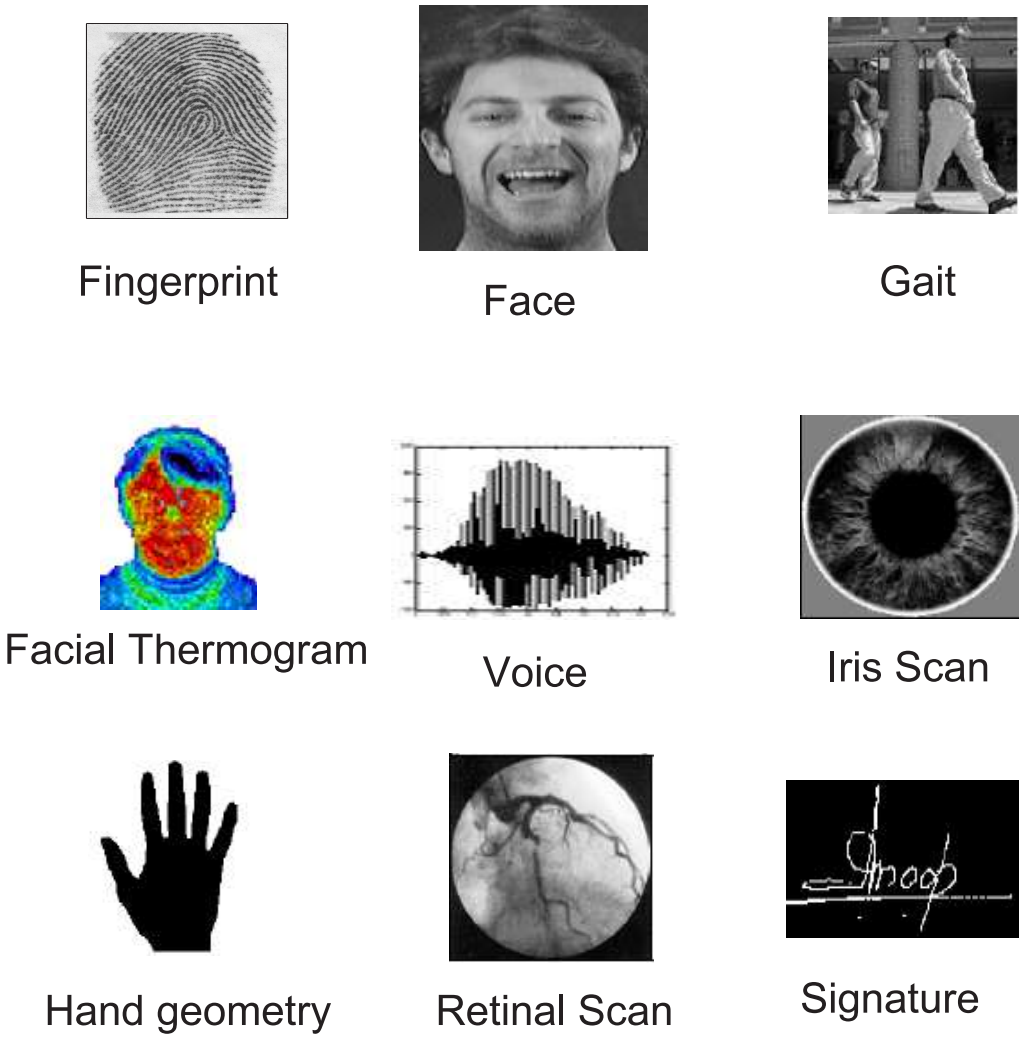


Figure 1.1: Examples of various biometrics

acquisition requires a high level of cooperation. This biometric is characterised from a high accuracy, but it is possible to deceive the system by presenting coloured contact-lents [Daugman 1993]. Moreover a recognition system based on iris is compromised by lighting variations such as intensity and directions and it is very costly because of the high quality of the capture devices.

Voice

Voice is very simple to acquire but it requires a deep enhancement pocess in order to extract the useful information to person recognition. In fact, the voice is strongly dependent on the environment conditions and on the humour of the person. Many voice-based identification systems have been proposed so far. Typically, the Fourier transform is the main feature extractor and the Hydden Markov Model the most successful algorithms for voice recognition [Furui 1997].

Facial Thermogram

The InfraRed technology can point out the thermal radiation of the human body. In particular, it is possible to obtain a feature pattern for characterising each person from the radiation intensity of the face [Prokoski 1992]. Unfortunately, such emission is dependent on many factors, in particular the person healthy and the presence of other objects in the scene. However, it can be useful to distinguish twins or drugged people.

Retinal Scan

The internal structure of the vein flows in the retina is unique for each person and can be used as a biometric [Hill 1978]. The main advantage is that it is practically impossible to steal or reproduce the retinal vasculature. However, the acquisition of such biometric is very expensive, more than the iris scanning. Moreover, the retinal vasculature is influenced from the healthy of the subject. Being characterised from a high accuracy, retinal vasculature-based systems are used in military applications.

Hand Geometry

Although the hand is not unique, it has been considered as a biometric and used for control access. The subject to be recognised places his/her hand on a panel. The hand is aligned through a system of pegs by outstrechting the fingers. Because it is not unique, the hand geometry cannot be used for recognising persons from a large population of identities. A variant of the hand geometry is the finger geometry, but its technology is not yet mature [Jain 1999].

Palmprints

Recently, person authentication through the epidermic ridge flow of the palm, called "palmprint", has been proposed. Recent results have shown that palmprints verification accuracy can be comparable with that of hand geometry [Zhang 2003]. Moreover, palmprints can be useful to increase authentication accuracy by combining them with oder biometrics [Kumar 2003]

Other physiological characteristics are the ear, body odor, the DNA. The

latter is widely used for criminal investigations and forensic applications, but its use for person authentication or recognition in civilian fields is strongly affected by its intrusiveness and the unreliability for positive identification. In [Jain 1999], Anil K. Jain, one of the greatest experts on biometrics, pointed out three limitations for a larger use of the DNA:

1. *it is easy to steal a piece of DNA from an unsuspecting subject to be subsequently abused for an ulterior purpose*

2. *the present technology for genetic matching is not geared for online non-obtrusive identification*

3. *the unintended abuse of genetic code information may result in discrimination in e.g. hiring practices*

Behavioural biometrics

It is acknowledged that the systems based on behavioural biometrics are less-robust than those based on physiological biometrics. The reason is that the behavioural biometrics can easly be reproduced by clever imitators. Moreover, they may be not invariant over the time, and they may be not unique. However, they can be used for authentication process in presence of a small user population.

We describe here briefly two of these biometrics: the signature and the gait. Other behavioural biometrics are the keystroke dynamics and the acoustic emissions during the signature scribble. Further details about behavioural biometrics can be found in [Jain 1999].

Signature: it is the widest used behavioural biometric. It is known that the signature is already accepted as an identity proof for all kind of docu-

ments, such as driver licenses, identity cards, commercial transactions. Being a behavioural biometric, it suffers from the physical and emotional conditions of persons. However, in the case of the signature, this kind of variations can be considered typical from person to person. Actually, the human experts can distinguish from the signature verification [Herkel 2003]. Recently, many systems based on signature have been proposed. This research field is still very active.

Gait: although it is relatively simple to capture, this biometric is very complex to process [Kale 2003]. Being a spatio-temporal-dependent biometric, its process requires very expensive computational resources. Moreover, it depends on the healty of person (e.g. drugs or Parkinson's disease affect dramatically such biometric).

1.3 Comparison between biometrics

Figure 1.2 shows the trade-off between accuracy and cost for the most important biometric systems.

The most accurate system is iris scan, but it is the most costly too, whether in terms of instruments' complexity for image extraction or in terms of difficulty of users utilization (intrusivity). These drawbacks are the reason of difficulties to the iris scan spreading.

Other methods, such as face recognition, are very few costly in terms of user collaboration and intrusivity. In fact, one can be shot inadvertently. Moreover, equipments to image acquisition are not expensive. The problem is that a sufficient accuracy to have developments and applications for a suitable diffusion is not yet achieved.

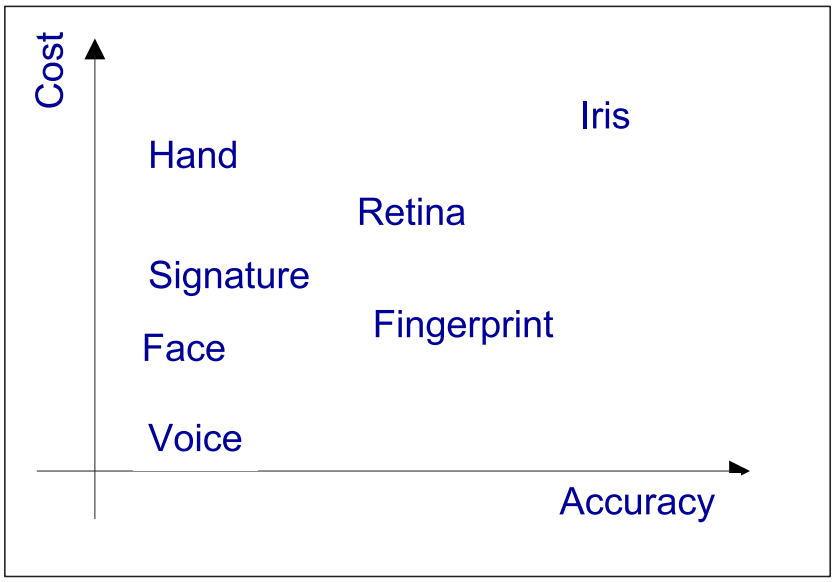


Figure 1.2: Trade-off between accuracy and costs for the main biometrics

Figure 1.2 shows that a good trade-off between accuracy and costs is achieved by fingerprint identification systems. Fingerprints are considered unique for each person, that is, don't exist two persons with identical fingerprints, even if the two persons are twins. Another advantage is that fingerprints are unalterable since the fetus is formed until the death. When the skin deteriorates, for esemple because of a wound, it reproduces identically to the old skin in a small time.

1.4 Biometric system structure

It is worth noting that biometrics have been widely used for criminal investigations and prisoners control from long time. The first system based on biometrics was proposed by Alphonse Bertillon in 1882. It was based on anthropological measures. It was used at the Leavenworth prison until 1903,

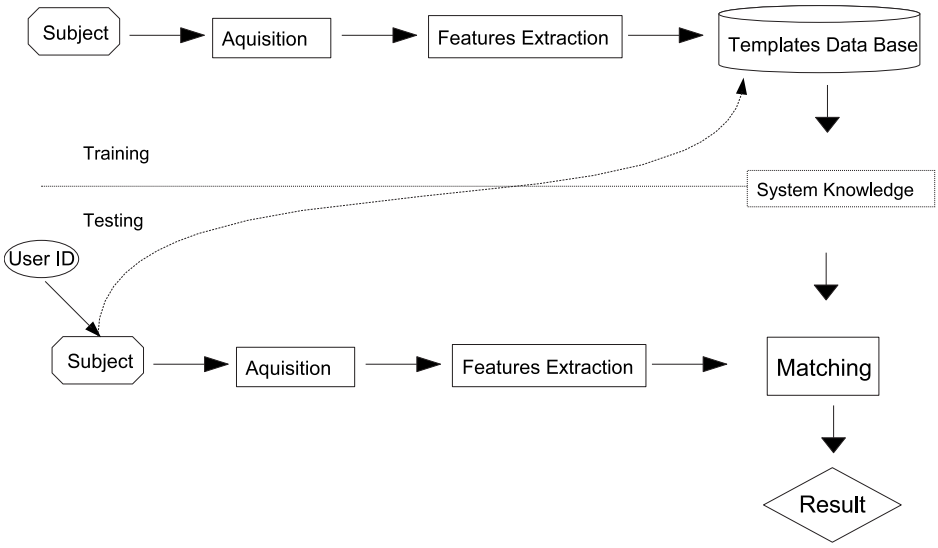


Figure 1.3: Architecture of a biometric system

when such system failed in distinguishing two twins. So far, many automatic identification systems based on biometrics have been proposed: in some case, the biometric technologies are notably improved from the first attempts and now they are very promising [Jain 1999]. Recently, some automatic verification systems based on fingerprint or face acquisition has been installed in airports and banks. Although such systems actually serve as deterrent, because their performance is yet low, their "active" presense could be considered an important step for the diffusion and the increase of the interest around the biometrics.

In the following we describe the general architecture of a biometric system. Figure 1.3 shiws such architecture. The first module of a biometric system is typically the *acquisition module*. The role of such module is to capture the given biometric: e.g. we could have an optical sensor for fingerprits or a camera for the face.

The second step is the processing of the capture biometric. Firstly, the biometric is processed in order to enhance the resolution of the captured signal (e.g. the face image). Then, a feature extraction is performed and the biometric is represented by its set of features (e.g. the iris-code for the iris). This is the so-called *template*, a mathematical model which serves as the biometric representation. The above processing and feature extraction phases are generally called *enrolment*. When a novel user has to be registered by the system administrator, she/he submits to the system his/her biometric and his/her identity. The biometric is processed and transformed in the template, that could be stored in the identities data base or in other means, as a smart card. The registration phase is tipically off-line.

The second phase of recognition[1] can be diveded in two main applications: the so-called identification and verification. In the first case, the subject submits to the system her/his biometric only. The role of the system is to find the most likely identity near to the possessor of the given biometric. This application is also called "indentification one to many", because the system must compare the given biometric with all those stored in the central data base (e.g. it is the case of criminal investigations). In the second case, the subject submits to the system her/his biometric and declares her/his identity. Figure 1.3 points out such case. In the example, the identity declaration is performed by a User ID. The role of the system is to verify that the declared identity and the "real" identity of the subject correspond. This application is also called "identification one to one", because the system must compare the given biometric with the template(s) of the claimed identity

[1]With the term *recognition*, we indicate in the following both identification and verification applications

stored in the central data base or in the smart-card submitted by the subject. This application appears to be simpler than indentification "one to many". However, it presents many problems, especially in defining the population of possible "impostors".

From the definitions given above, it is evident that the "enrolment" phase is common both in the registration and in the recognition phases. In the first one, he subject is registered for the first time into the system, while in the second one the subject must be identified by the system on the basis of previous registration. The difference is that during the registration phase the system *has* the subject identity. In the identification case, the system has to identify or to verify the identity of the subject given his/her biometric.

The core of a biometric system is the identification module, i.e. the algorithm used for comparing the template stored in the data set and the input biometric submitted in a second time. For each biometric, the literature presents many works for performing such comparison. The final result of the so-called "matching" phase is a real value named *distance* or *score*. The score value is the degree of similarity between the input biometric and the template. The maximum value means that the two biometrics are the same, the minimum value value means that the two biometric are definitely different. Vice versa for the distance.

In the "one to many" identification, usually all possible identities whose input-template comparisons exceeded a given threshold are considered, and the final decision is trusted to human operator.

In the identification "one to one", if the score is more than the so-called "acceptance threshold", the subject identity is verified and the person is

classified as a "genuine user". Otherwise, the subject is classified as an "impostor".

In some systems the identification module could be very complex, especially in the case of "one to many" identification. In this case, many comparisons should be performed (e.g. the FBI fingerprint data set contains more than 70 milion fingerprint images!) and the identification time could be very large. However, if it is possible to group in classes those images exhibiting similar textures or shapes, as the fingerprints, the problem could be notably simplified and the identification time could be drastically reduced. In fact, before identification, a *classification* step is performed by comparing the given biometric through a mathematical model representing each class. After classification, the system compares the given biometric only with the ones belonging to the computed class or classes. In certain cases, the difference among classes are not well-defined. As a consequence, more than one class could be associated to the given biometric. It is the case of the fingerprints.

We deeply study and investigate only the classification issue suggesting various methods to design the fingerprint biometric systems and comparing them with other approaches described in literature to do it.

1.5 Requirements of a biometric system

In the following we give some requirements for each biometric system. Such requirements vary in function of the biometric system.

- *Co-operative:* the system needs the user co-operation. As an example, an iris based biometric system needs that the user places his-self in a

certain position with respect to the camera

- *Evident:* the system is not hidden to the pubblic. It is the case of biometric systems for access control based on fingerprints
- *Habitual:* the system is frequently used. E.g. a biometric system for accessing to the user PC
- *Public:* the system is accessible to many different users
- *Standard environment:* the system does not modify the environment in which it is placed
- *Open:* the system communicates information with other systems.

1.6 Biometric system evaluation

The objective evaluation of a biometric system is still a matter of on-going discussions. Intuitively, such performance can be defined as the rate with which the system correctly associate or verify people identities. Such performance is strongly dependent on the environmental conditions and, in many cases, on the people healthy (with this term we mean both physiological and emotional states). The environmental conditions are the weather, the temperature, the background with respect to which the biometric is captured (e.g. face, gait, etc.). The physiological or behavioural conditions are the state of the biometric (e.g.. fingers or hands could be moist), the subject appearance (e.g. contact lens for the iris, glasses for the face), or his humour (e.g. face expressions).

Moreover, many open issues concern the change of the biometric over the time, that may cause large variations of the target population. All these parameters concur to deceive a biometric system even if the identification should appear to be straightforward for human operator. Therefore, the main issues to consider for a correct system evaluation are *the environment where the system is expected to work*. In this case, the term "environment" means not only the system physical location, but also the kind of population that is expected to use (or to fraud) it. As such issues have been considered, it is possible to indicate some fixed points for evaluating recognition and verification systems [Jain 1999] [Mansfield 2002].

In the case of identification "one to many", or simply "identification", two parameters are important to evaluate the performance:

1. the overall accuracy, usually given in terms of ratio between number of correct identification and number of total comparisons

2. the Cumulative Match Characteristic (CMC), also referred as Rank Curve. The CMC represents the overall identification accuracy when the number of possible identities considered by the system increases. In other words, the CMC plots the verification accuracy in function of the first k identities in the data base. Such identities are associated to the patterns "closest" to the input biometric. A system exhibiting the slope of such curve superior than that another system is obviously more reliable

Where it is possible to perform a preliminary biometric classification, the overall *classification* accuracy is the usual evaluation parameter. Such parameter is computed by ratio between the number of correctly classified

samples and the number of samples submitted to the system. Another evaluation parameter is the so-called *penetration rate*. The penetration rate is a measure of the average portion of the whole data base that is used during identification (matching), and strictly depends on the classification accuracy. The general definition of penetration rate is:

$$P = \frac{E(NumberOfComparison)}{N}$$

where N is the total number of templates in the data base and $E(NumberOfComparison)$ is the expected number of comparisons for a single input sample [Jain 1999]. Unfortunately, such parameter does not always reveal actual advantages of the system, especially regarding the reduction of the identification time.

In the case of identification "one to one", or simply "verification", the so called verification score s provides the degree of similarity between two biometric patterns, and take values in $[0, 1]$. The higher the score, the higher the similarity degree between the considered patterns. A biometric pattern belongs to the *genuine class* if the identity of her/his possessor corresponds to the claimed one. The opposite holds for the *impostor class*.

The design of any biometric verification system depends on the estimate of the two posterior probabilities $p(s|genuine)$ and $p(s|impostor)$, and the selection of the *acceptance threshold* $s*$. If the score is higher than the acceptance threshold, the claimed identity is accepted and the person is classified as a genuine user. Otherwise, she/he is classified as an impostor.

Authentication errors obviously depend on the acceptance threshold. They are called "false acceptance" errors if an impostor is accepted, and "false rejection" errors if a genuine user is rejected. The probabilities of false ac-

ceptance and false rejection are called False Accenptance Rate (FAR) and False Rejection Rate (FRR). The FAR and FRR mathematical expressions are as follows:

$$FAR(s*) = \int_{s*}^{1} \big(p(s|impostor)ds\big)$$

$$FRR(s*) = \int_{0}^{s*} \big(p(s|genuine)ds\big)$$

In the two equations the value s* is the so-called "acceptance threshold". Because of the dependance of FAR and FRR on the threshold, the literature proposed some FAR and FRR measures in some important points:

- Equal Error Rate (EER)point. It is the point where FAR(s*)=FRR(s*)
- 1%FRR (1%FAR). It is the FAR (FRR) corresponding to the threshold for which the FRR (FAR) is fixed to 1%
- ZeroFRR (ZeroFAR). It is the FAR (FRR) corresponding to the threshold for which the FRR (FAR) is fixed to 0%

In general, the threshold value depends on the application for which the biometric system is designed. Then, the choice of the evaluation point (i.e. the evaluation "fairness") has to be regarded with respect to expected environment. As an example, for a control access system in a nuclear power station, a high performance in terms of FAR are required without denying the access to authorised persons (low FRR). For such system the 1%FRR or the ZeroFRR are measures more critical than the EER.

The so-called Receiver Operating Characteristic (ROC) shows the general performance level of the system in terms of graphical view. The ROC is the

graph of the couple $\{FAR(s*), FRR(s*)\}$ for all the acceptancce threshold values.

Before closing this section, it is worth noting that the conceps of FAR and FRR describe the performance of the system by including in some case the errors in the enrolment phase. An error in the enrolment phase occurs when the biometric cannot be acquired or not processed or not make suitable fot the template computation. In this case this kind of errors affects the FAR and the FRR evaluation. In order to separate the "enrolment errors" and to assess the effectiveness of the matching algorithm, False Matching Rate (FMR) and the False Non-Matching Rate (FNMR) terms have been proposed instead of FAR and FRR, respectively. The plot of the couples $\{FMR(s*), FNMR(s*)\}$ have been then called Detection Error Trade-off curve (DET). FMR, FNMR, DET curves refer to the error rate of the system when enrolment errors are not considered. However, very few papers in the literature use such terms (as very few vendor give it in their data sheet). Further details about "best practices" in evaluating biometric systems can be found in [Mansfield 2002].

1.7 Fingerprint biometric

1.7.1 History of fingerprint recognition

The high discriminative power of fingerprints seems to be known by Chinise population since 7000 b.C. Fingerprints have been systematically studied, with scientific criteria, since the XIX century [Maltoni 2003], [Jain 1999]. In the XX century, the structure and the main features of fingerprints have been

pointed out thanks to researchers as Galton and Henry [Henry 1900]. It is worth noting the increase of the success of fingerprints for personal recognition has involved the academic, the industrial and the forensic communities. The main steps can be summarised as follows:

- from 1684 to 1788, European scientists as Grew, Malpighi and Mayer published the first studies on the structure of ridge and valleys of fingerprints
- in 1809, the entrepreneur T. Bewik started to use his fingeprints as trademarks
- from 1823 to 1899, fingerprints have been rigorously described by Herschel, Faulds, Galton and Henry
- in 1901-02, fingerprints were adopted by Scotland Yard for criminals categorisation. In particular, in 1902 the first case was solved thanks to fingeprints left in the crime scene
- in 1960, the first Automatic Fingerprint Indentification System (AFIS) were adopted by the FBI and the Paris Police Department
- in recent years, the National Institute of Standard and Technology (NIST) fixed the standard definitions of fingerprint characteristics

Nowadays, to the state of our knowledge, the technology for acquiring, processing and matching fingerprints can be considered as a mature technology. So, fingerprints have been widely proposed both in forensic and civilian applications. However, it is very difficult to design an automatic fingerprint

classification and identification system exhibiting very high recognition accuracy and reliability. So, fingerprint recognition is still a very active research field.

1.7.2 Structure of fingerprints

Fingerprint patterns are described by the epidermic ridge and valleys. As mentioned in section 1.3, two properties concurred to the wide success of fingerprints for personal recognition: the persistence and the uniqueness.

- *Persistence* means that the ridge pattern does not change over the time
- *Uniqueness* means that such ridge pattern is unique from person to person. Moreover, fingerprints cannot be forgotten and it is very difficult to stole and reproduce them

The persistence and the uniqueness are two very important properties of such biometric. It is worth noting that persistence has been scientifically proved; even in case of intensive manual works, the ridge pattern forms again after few days of rest; but the uniqueness is still matter of on-going research. Usually, the uniqueness is "proved" by empirical and statistical observations. From the empirical point of view, it is easy to see that not a couple of twins have the same fingerprints. Statistically, it has been shown that the probability of exhibiting the same minutiae set among two fingerprint is about 6×10^{-8} [Pankanti 2002], [Bolle 2002]. The minutiae are micro-characteristics that allow to distinguish two fingeprints (see the related sub-section in 1.7.2).

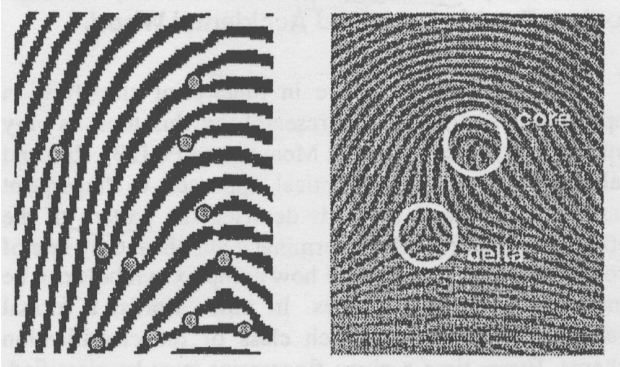


Figure 1.4: Main characteristics of a fingeprint image. In the left are emphasized the micro-characteristics (minutiae points), in the right are emphasized the macro-characteristics (core and delta points)

Macro-characteristic of fingerprints

The "macro-characteristic" of fingerprints, or "global features", are constituted by the ridge pattern and the "singularity points". Such features are not sufficient to distinguish two fingerprints. However, they greatly simplify the whole identification process.

The ridge pattern characterises the shape described by the ridge flow. The singularity points are localized in small regions where the ridge flow becomes irregular. In particular, we can defines two singularity points: the *core* point and the *delta* point. In the first case the ridge flow describe a circle usually localized at the center of the ridge pattern. In the second case the ridge lines converge and describe the "Δ" greek letter. The right side of the Figure 1.4 shows an example of core and delta points in a fingerprint.

In a fingerprint it is possible to find one or two delta points and one or two core points, although these latter are always localized at the center of the shape. Through the relative position among such points, Edward Henry

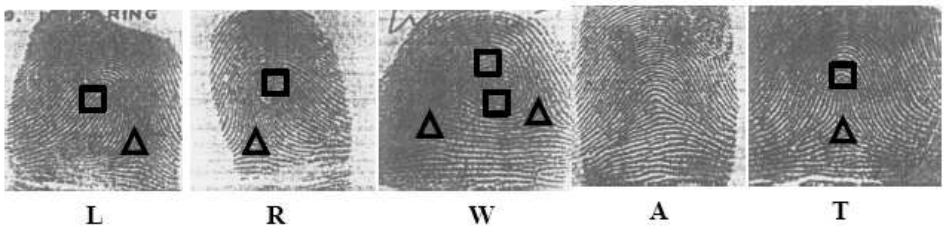


Figure 1.5: Examples of the five fingerprint classes [3]: (L) Left Loop (R) Right Loop (W) Whorl (A) Arch (T) Tented Arch. Core and delta points are shown for each class in this figure by squares and triangles, respectively. The A class has no singularity, the L, R, T classes have two singularities (one core and one delta point), and the W class has four singularities (two cores and two deltas)

had been able to identify eight categories of ridge pattern among fingerprints [Henry 1900]. These eight categories are plain arch, tended arch, radial loop, ulnar loop, plain whorl, central pocket, double loop, accidental whorl.

Such categorisation has been simplified to four or five classes by the National Institute of Standard and Technology (NIST). In particular, the plain arch, central pocket, double loop and accidental whorl classes have been grouped in the whorl class; the plain arch and the tended arch classes have been grouped in the arch class. Radial loop and lunar loop are also called right loop and left loop classes, respectively. The categorisation with five classes uses the plain arch (simply, arch), tended arch, right loop, left loop and whorl classes, while the categorisation with four classes uses the arch, right loop, left loop and whorl classes. Figure 1.5 shows the selected five classes.

Such categorisations allow to greatly simplify the problem of the search

for a fingerprint in a data set. In fact, it is firstly possible to identify the class which a certain fingerprint belongs to, and secondly to perform a search in the subset made up of fingerprints of the identifies class.

By reducing the minimum the number of classes, i.e. by considering arch, left loop, right loop and whorl classes, we can notice the following characteristic:

- the arch class exhibits only one core and no delta points
- the left loop class exhibits one core point and one delta point localized at the right of the image
- the right loop class exhibits one core point and one delta point localized at the left of the image
- the whorl class exhibits two core points and two delta points

These features allow to classify a fingerprint image in a simple way. However, the boundaries among classes are very smoothed, so it is possible to have a fingerprint with a ridge pattern similar to the one of more classes. Such fingeprints are usually referred as *cross-referenced* because they are labelled with more than one class (e.g. arch and left loop). They cannot be assigned to one class neither by a human expert.

Therefore, although all AFIS systems require the fingerprint classification stage before the matching stage, it is very difficult to design an automatic system able to perform such classification with high accuracy [Karu 1996].

Micro-characteristics of fingerprints

The micro-characteristics of fingerprints, or "local features", are constituted by the discontinuities of the ridge lines, usually called *minutiae points*. So far, about 150 types of minuitiae points have been founded [Lee 1994]. Usually, the various kinds of minutiae points are grouped in two types: the bifurcation and the termination of the ridge lines. Figure 1.4 shows this kind of minutiae.

Such points describe in detail each fingerprint, that is, the fingerprint image can be substituted by its minutiae set without loss of information. The position and orientation of minutiae are claimed to be unique from person to person. Therefore, they are the main features used in identification (matching) process. The definition of the position and orientation have been fixed by the NIST. In particular, the orientation is defined as the local orientation of the ridge line which the minutia belongs to.

To manually match two fingerprints through their minutiae points is a very difficult and tiring process. So, various algorithms for automatic matching based on minutiae heve been proposed. Obviously, none of them is able to certify the two fingerprints matches perfectly. However, their use allowed to notably simplify the identification process in criminal investigations, and in the simpler case of access control.

1.7.3 The Automatic Fingerprint Identification System

Figure 1.6 shows an overview of a fingerprint identification system. The first module is aimed to acquiring the fingerprint image. The second module

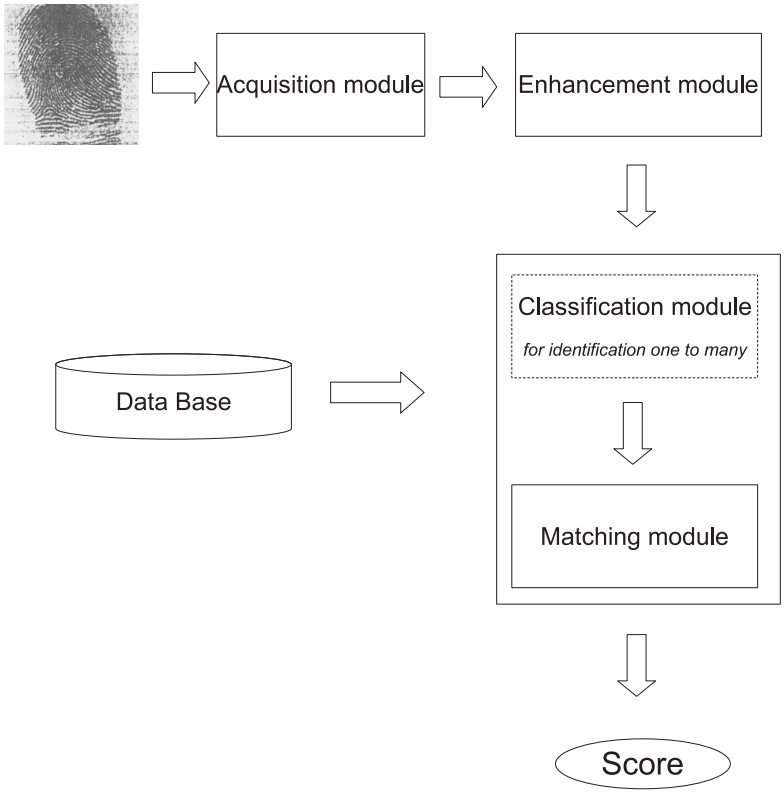


Figure 1.6: The Automatic Fingerprint Identification System (AFIS) scheme

typically enhances the quality of the acquired image. The third module performs the preliminary classification of the fingerprint, i.e., it assign a class among those viewed in section 1.7.2. The fourth module is the matching module. It performs a comparison between the input fingerprint and the ones stored in the fingerprint database and associated to the class(es) computed by the classification module.
The output of the matching module is a score, i.e. a similarity degree from the compared fingerprints. Such score can be used in two ways:

- if the identification one to one is performed, such score has been derived from the comparison between the given fingerprint and the template fingerprint associated to the claimed identity. In other words, the person to be recognised by-passes the classification module by declaring his/her identity. In this case, if the score exceeds a certain fixed acceptance threshould, the claimed identity is "verified").

- if the identification one to many is perfomed, the score value is associated to a certain identity. By ordering the identities in fuctions of the increasing order of their score, the system returns the most probable identities which the inpunt fingerprint belongs to).

This thesys study deeply the classification module used for the identification one to many. We investigate novel algorithms to fingerprint classification and their fusion, whether among themselves or among other important approaches proposed in literature. Next chapter describes the state of the art of fingerprint classification approaches, with particular attention to statistical and structural ones.

Chapter 2

Fingerprint Classification: State of Art

The simplest way to classify a fingerprint is to localise their core and delta points. By counting the number of such singularities, it is possible to identify the class which the fingerprint belongs to. Karu and Jain [Karu 1996] present a simple classification system based on such computation. Unfortunately, this approach does not work well if the image is significantly corrupted by the noise, that does not allow to reliably localize the singularities points.

Due to the above limitations, the most of the proposed approaches to automatic fingerprint classification are only partially based on the singularities detection (e.g., on the detection of the core point), and try instead to extract global features related to the ridge flow orientations. To this end, many classification algorithms compute the so-called *orientation field*, which is the map of the ridge-flow average orientations of the fingerprint image. Figure 2.1 shows an example of orientation field extracted from a fingerprint image.

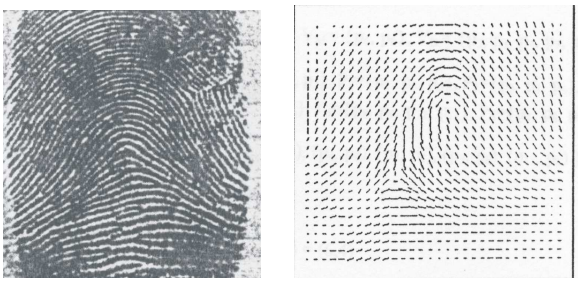


Figure 2.1: Example of fingerprint image and corresponding orientation field. In the example, the original image is 480x512 pixels sized. Each pixel of the orientation field has been computed with a 32x32 pixels sized block of the original image, so generating a 28x30 pixels sized orientation field

So far, many approaches for fingerprint classification have been proposed. They are based on different pattern recognition teories. Main approaches are:

- **Statistical methods:** are based on the identification of singular points (core and delta points). The used criteria for singularities computing are assentially euristics and the success for finding them is strongly affected by noise. In fact, in the cases in which the noise is very high, it is possible to not take delta or core points, or take them in incorrect positions. This kind of methods transform patterns in a features vector of fisical and real characteristics.

- **Geometrical methods:** are based on geometrical approssimation of the ridge. As an example, we mention the method of Ghong [Ghong 1997] that use the B-splines.

- **Syntactical methods:** among the first methods devised, they date from the Seventies. The basic idea consists in associate at each class a grammar that describes the fingeprint. Each fingerprint is coded as

a phrase. Then a syntactical analysis is performed and finally it is associated to the grammar of which the phrase respects the rules, that is, the fingerprint is classified.

- **Structural methods:** innovative methods that exploit the structure of the pattern and trasform them in structural data.

- **Neural methods:** methods that exploit a neural network as fingerprint classifier. A neural network can be a simple perceptron, a multilayer perceptron (MLP) or a more complex architecture as a recursive neural network (RNN).

For the purposes of this work, the proposed approaches to fingerprint classification can be subdivided into the two main categories of statistical and structural approaches.
Statistical methods are characterised by the use of the decision-theoretic approach to pattern classification [Duda 2001], namely, a set of characteristic measurements, called feature vector, is extracted from fingerprint images and used for classification [Candela 1995]-[Yao 2003].
Structural approaches basically use the syntactic or structural pattern recognition methods [Moayer 1975]-[Neuhause 2005]. Fingerprints are described by production rules or relational graphs, and parsing processes or graph matching algorithms are used for classification.
Recently, the fusion of multiple fingerprint classifiers has been proposed [Yao 2003], [Senior 2001]-[Neuhause 2005 b].

2.1 Statistical methods

Statistical methods use a vector of statistical measures to represent the fingerprints. In [Ghong 1997] the sequence of the B-splines coefficients was used in order to approximate the orientation field, i.e. the orientation of the skin ridge flow, and an empirical rule is used to perform the final classification. In [Candela 1995] the researchers of the National Institute of Standard and Technology (NIST) proposed a method based on the KL-transform of the orientation field (the representation of the fingerprint). A probabilistic Neural Network is used for elaborating the obtained pattern and for making the final classification.

In [Jain 1999 b] each fingerprint is described in terms of *fingercode*. We describe this method with more details because we used it for comparison and fusion with our methods. The core of such approach is a novel representation scheme (called "FingerCode") which is able to represent into a numerical feature vector both the minutiae details and the global ridge and furrows structures of fingerprints. The computation of such FingerCode starts by identifying the "core" point in the fingerprint input image and by defining a spatial tessellation of the image region around this point. This spatial tessellation is a circle decomposed in 48 sectors. Then, four band-pass Gabor filters with orientation-selective characteristics ($0^0, 45^0, 90^0$, and 135^0) are applied to such tessellated image, so producing four orientation-filtered images. Each filtered image accentuates ridge structures along one orientation. Finally, for each filtered image and for each sector, the standard deviation of grey level values is computed, and the FingerCode feature-vector with 192 elements is produced. Jain and his collaborators used such feature vector as input to

a two stage classification architecture using a K-nearest neighbour classifier to find the two most probable classes of fingerprints and ten binaries neural networks to make the final decision (see Figure 2.2).

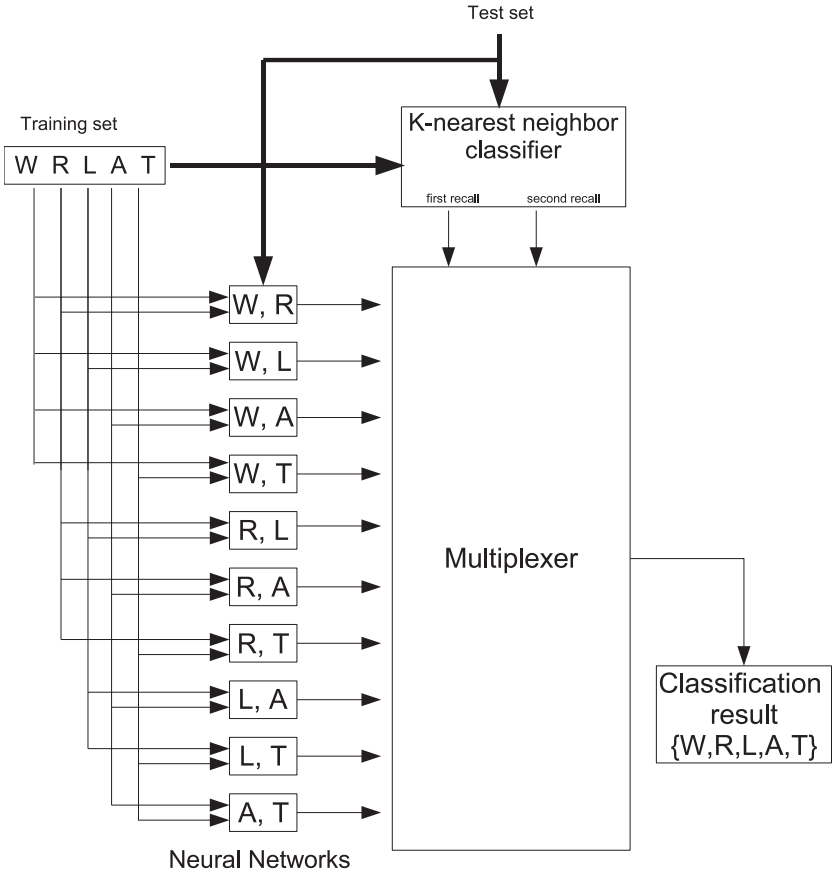


Figure 2.2: The Multichannel approach to fingerprint classification proposed by Jain et al. [Jain 1999 b]

We used such feature vector as input of a multi-layer perceptron (MLP).

2.2 Structural and graph-based methods

The structural approaches describe the fingerprint in terms of grammars or graphs.

Moayer and Fu (1975) [Moayer 1975] and Rao and Balk (1980) [Rao 1980] give a syntactical description of the fingerprint, by defining a set of terminal symbol, based on the "local structure" of the skin ridges, and a set of production rules to create a grammar that represents each class. A parsing algorithm is applied to perform the final classification. These kind of approaches are the oldest, and they have been dropped by the modern research, because of their sensitivity to the noise frequently added to the fingerprint images during the acquisition process.

In Cappelli et al (1999) [Cappelli 1999] an adaptative filter, called "dynamic mask" and correspondent to each class is applied to the orientation field in order to segment it. In the following we describe deeply this method because we use it for comparison and fusion with our ones.

This method was introduced to overcome the large variability of segmentations of similar fingerprints, which comes out when the segmentation algorithm described in [Maio 1996] is applied. The basic idea of this approach is to perform a "guided" segmentation of the orientation field of the fingerprint image in order to reduce the variability during the segmentation process.

To this end, five filters, called "dynamic masks", one for each class, "guide" the orientation field segmentation, so producing a class-dependent segmentation. Such dynamic masks can be regarded as "prototypes" of images segmented by the orientation field. Using these filters the number of seg-

mentation regions and the coarse region shape are fixed. Each dynamic mask is obtained by the following four steps:

1. for each class, selection of a set of representative fingerprints
2. computation of the respective orientation fields
3. application of a genetic algorithm to segment the orientation field
4. identification of an "average" ensemble of fixed and mobile vertices and segments that define the mask. Such vertices are located around the singularity points ("core" and "delta")

To classify fingerprints, the orientation field of an input fingerprint is segmented according to the five dynamic masks (one for each class). For each mask, a "cost" provides a measure of the difficulty of the guided segmentation process. Accordingly, the lowest cost means that the segmentation process can easily produce a segmented image very similar to the used mask. The cost vector is then converted into a posterior probabilities vector. The class associated to the maximum posterior probability is associated to the fingerprint.

In Lumini et al. (1999) [Lumini 1999] the orientation field of a given fingerprint image is computed. A segmentation is performed in order to partition the orientation field in "homogeneous orientation" regions. A relational graph is defined by starting from the segmentation. Finally an unelastic matching with a template graph for each class is performed and the best match determines the final classification.

In Yao et al. (2003) [Yao 2003] the fingerprint is described by a Directed Oriented Acyclic Graph, and a structural vector is extracted from the given

graph and merged with the "fingercode" of the original image. A set of Support Vector Machines (SVMs) is trained and the outcomes of each classifier are combinated through an Error Correcting Output Code System, in order to make the final decision. This system presents a better accuracy rejection curve with respect to that reported in [Jain 1999].

Senior [Senior 2001] proposes a fingerprint classification system based on the integration of hidden markov models (HMM) and decision trees (DT). The HMM-based classifier is trained by a set of novel features extracted from the skin ridge flow. Such feature extraction step is performed as follows. A set of horizontal and vertical "fiducial" lines intersects the skeletonised fingerprint image at different locations. At each 'fiducial line'-'ridge line' intersection, a set of measures is computed. A multi-layered HMM is designed by considering the so-computed set of features at each fiducial line as the input of each layer. The decision tree classifier is trained on another set of features extracted from the skin ridge flow. Such features are aimed to encode the ridge shape. The outcomes of the DT and HMM classifiers are the inputs of a feed-forward neural network for the final classification.

A graph matching based approach using directional variance is recently proposed by Neuhause and Bunke (2005) [Neuhause 2005]. It consists on computation of a directional variance measured at each pixel of orientation field. The variance is defined such that high variance areas correspond to relevant regions to discriminate between fingerprint Henrys classes. These regions are not only singular points, but also areas with vertical ridge orientation. The resulting structures are converted into attributed graphs. A node corresponds to a pixel of the selected high variance regions and the edges are

the connection among the pixel. The attributes are the position of the corresponding pixel as node feature and an angle information as edge feature. In order to perform the classification, a K-Nearest Neighbour paradigm is applied. The edit distance is based on a simple cost function in which constant costs are assigned to insertion and deletion operations and a value proportional to the Euclidean distance of attributes is assigned to costs of substitution operations. In order to find the minimum path for the edit distance, only a subset of all edit paths is considered in the approximate algorithm, instead of exploring the full search space. The prototypes set is established by manually selecting promising candidates. It consists of 60 elements.

2.3 Multiple classifiers system to fingerprint classification

So far, the works [Jain 1999], [Yao 2003], [Cappelli 2002], [Nagaty 2001] and [Neuhause 2005 b] are the only ones in which a multiple classfier system is used for the performance improvement. In particular, [Cappelli 2002] use the "dynamic masks" method as first classifier.

Moreover, a novel transformation of the orientation field, called Multiple KL-tranform (MKL), generates a feature vector for each fingerprint. Two classifiers (Nearest Neighbour and a K-Nearest Neighbour) are trained by using the MKL transformation, and the decisions of the Dynamic Mask method and the two classifiers described above are finally combined by using the majority voting rule [Windeatt 2003].

Nagaty (2001) [Nagaty 2001] proposed the combination between statistical

and structural features at the level extraction. The structural features are represented by the orientation field codified into a binary string of fixed dimension. The statistical features are represented by a "texture measure" performed by the computation of the second moments. A feature vector made up of the whole statistical and structural features (186 features) is the input of a Artificial Neural Network which performs the final classification.
A very recent work is proposed by Neuhause [Neuhause 2005 b]. The fusion is performed by generating a unique graph from different graph representations of each pattern. Each representation is obtained by different approaches. For each pattern, the two most similar graphs are searched for, then they are merged to obtain one graph. The process iteratively continues until all graphs are reduced in only one graph.

Chapter 3

A Graph-Based Approach to Fingerprint Classification

3.1 Introduction

Fingerprint classification is based on the shape described by the skin ridges flow of such biometrics: Arch (A), Tended Arch (T), Left Loop (L), Right Loop (R) and Whorl (W). The next step is to recognise the fingerprint by performing a search in the set of fingerprints associated to the identified class (matching process). This strategy is necessary for reducing the identification time.

Unfortunately, fingerprint classification task is made very difficult by several factors. Among the others, the poor quality of real fingerprint images which can decease the singularity points detection, and the existence of ambiguous fingerprints which cannot be reliably classified even by human experts. In particular, the crucial issue of ambiguous fingerprints is due to the large within-class variability and the small between-class separation. In some

cases, fingerprints which cannot be reliably assigned to a single class even by human experts are labelled with two classes, and named "cross-referenced" fingerprints. These fingerprints are so called because two classes, instead of one, are associated to them. Figure 3.1 shows an example of "AT cross-referenced" fingerprint, beside a A and a T fingerprint. Because of the shape "continuity" among classes, it is impossible to associate only one of them.

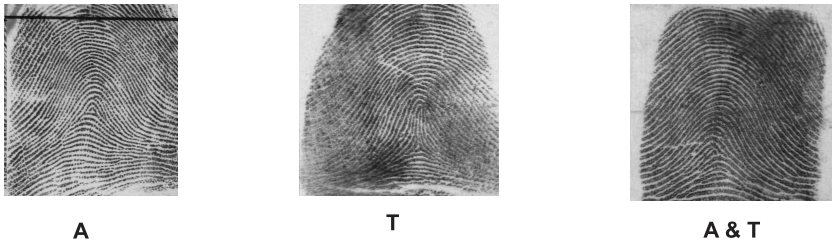


Figure 3.1: Example of AT cross referenced fingerprint compared with A and T fingerprint images

As said in Chapter 2, the proposed approaches to automatic fingerprint classification can be coarsely subdivided into two main categories of "flat" and "structural" approaches. Flat approaches are characterised by the use of the "decision theoretic" or statistical approach to pattern classification, namely, a set of characteristic measurements, called feature vector, is extracted from fingerprint images and used for classification ([Candela 1995], [Jain 1999], [Nagaty 2001], [Senior 2001], [Cappelli 2002]). On the other hand, structural approaches presented in the literature basically use the syntactic or structural pattern recognition methods ([Moayer 1975], [Rao 1980], [Cappelli 1999], [Lumini 1999], [Yao 2003], [Neuhause 2005 b]). Fingerprints are described by production rules or relational graphs and parsing processes or graph matching algorithms are used for classification. It is worth re-

marking that the structural approaches of fingerprint classification has not received much attention still now. However, a simple visual analysis of the structure of fingerprint images allows one to see that structural information can be very useful for distinguishing fingerprint classes of the arch and whorl type. On the other hand, it is easy to see that structural information is not appropriate for distinguishing fingerprint classes of the right loop, left loop and tended arch type. Figure 3.2 shows a typical segmentation of each class. Accordingly, the combination of flat and structural approaches should be investigated. With regard to this issue, it is worth noting that very few papers in the literature investigated the potentialities of such combination ([Nagaty 2001], [Cappelli 2002], [Yao 2003], [Neuhause 2005 b]).

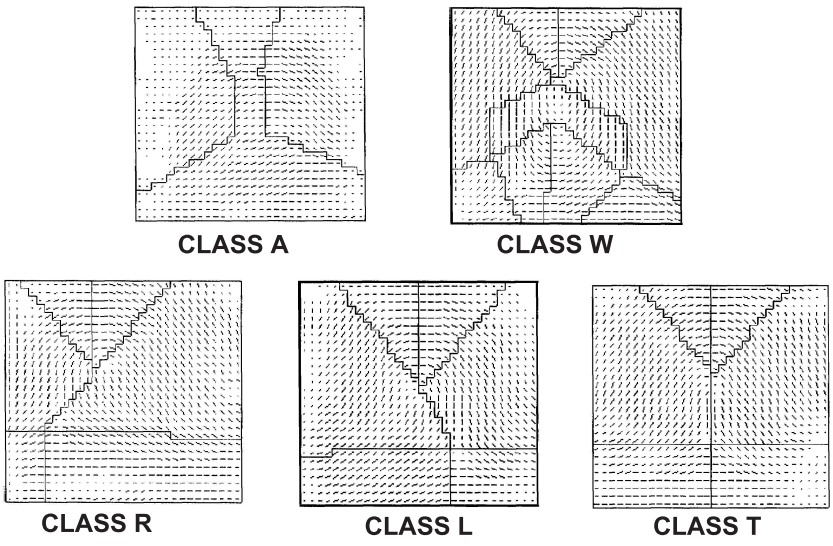


Figure 3.2: Segmentation of the orientation fields of the fingerprint images for the five Henry's classes

3.2 An appropriate data representation

According to section 1, our definition of fingerprint structure corresponds to the topology of completely connected "regions" grouping ridges and valleys with homogenous orientations. Such topology relies on the singularities locations. Hence, it is different from class to class, according to the Henry's classification [Henry 1900].

The so defined fingerprint structure can be easly extracted by segmenting the fingerprint orientation field into regions characterised by homogeneous ridge directions ([Yao 2001], [Yao 2003], [Lumini 1999], [Cappelli 1999], [Marcialis 2001], [Marcialis 2003]).

The first problem is how to describe such structure through an appropriate data type. The relational graph appears to be an appropriate type of data for describing the fingerprint topology. The relational graph nodes could correspond to regions extracted by the segmentation algorithm, as shown in [Lumini 1999]. However, the main arising issue is to find the best representative graph for each fingerprint class, in order to apply a template-matching algorithm, like such shown in figure 3.3. In particular, L, R and T classes, fingerprints structures are very difficult to separate by a simple relational graph-based representation.

The second problem is to make the above fingerprint representation "robust" to the large small-within class variability and the small between-class variability, which is accentuated in real applications because of the noise in sensed data. Because each region derives from the segmentation algorithm, the robustness degree is mainly dependent on such algorithm. However, to the best of our knowledge, none of the proposed segmentation algorithms

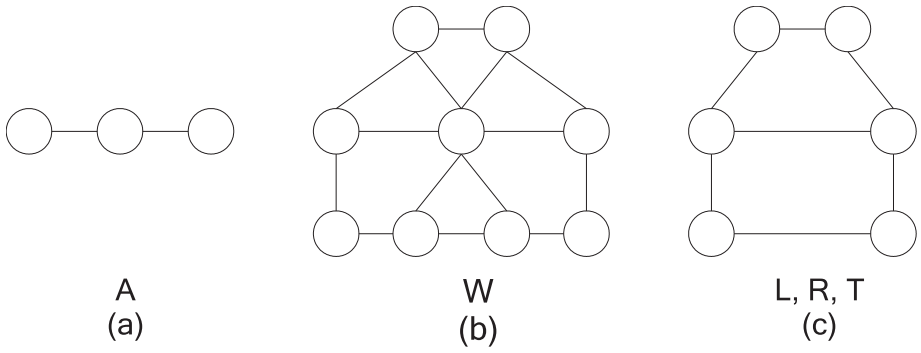


Figure 3.3: Some example of relational graphs representing the structure of A, W, L, R, T classes, according to segmentations of Figure 3.2. Each node corresponds to each segmentation region. Edges are drawn according to adjacency of related regions. While it is simple to describe A and W classes (a-b), it is quite difficult to separate L, R and T classes on the basis of their structure by using a relational graph (c)

is robust to the above variability. As a consequence, very different segmentation related to fingerprints of the same class and similar segmentations related to fingerprints of different classes (L, R, T and W especially) are produced [Lumini 1999], [Cappelli 1999].

The structural classification system presents the same general architecture of all pattern recognition systems [Duda 2001]. Figure 3.4 summarises such architecture. It is made up of:

- a pre-processor module to enhance the quality of the input fingerprint image and to generate the orientation field segmentation

- graph generator module, which takes as input the orientation field segmentation provided by the previous module. Each node of the graph is enriched by a real-valued feature vector extracted from the orientation field. We used two graph representation; a generic relational graph and a DPAG, namely, Directed Acyclic Positional Graph.

- an appropriate machine learning model for each data representation: a classical graph-based classifier, based on inexact graph matching theory and a Recursive Neural Network for classifying the fingerprint. These methods takes as input the graph representation generated by the previous module, respectively.

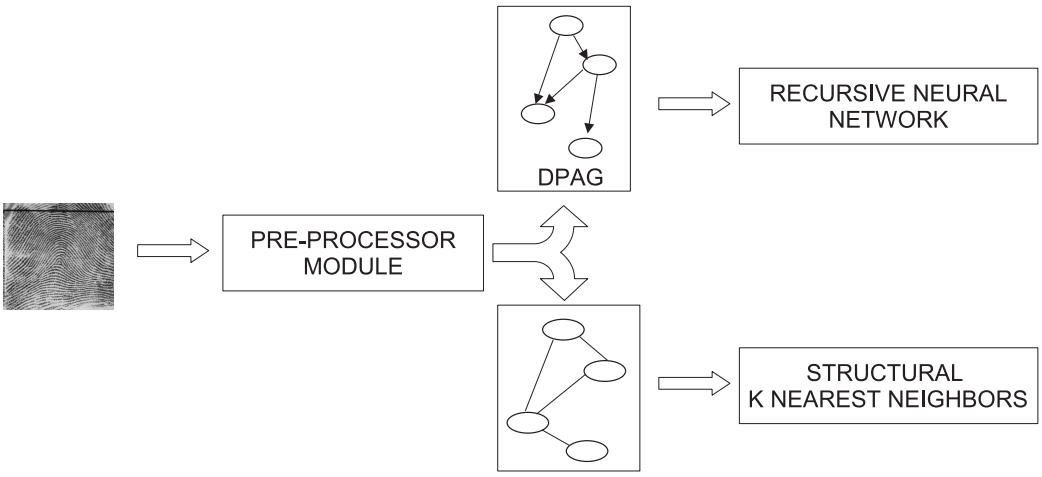


Figure 3.4: Modules of our fingerprint classification system

3.3 The pre-processor module

The pre-processor module performs the enhancement, the orientation computation and the segmentation of the fingerprint image, as shown in Figure

3.5. The enhancement and the orientation field computation is performed by using the algorithms proposed in [Candela 1995], while the orientation field segmentation is performed by using the algorithm proposed in [Maio 1996]. The aim is to partition the orientation field into regions characterised by homogeneous ridge directions. The used algorithm implements a very sophisticated "region growing" process. It starts from the central element of the directional image and scans the image according to a square spiral strategy. At each step, the segmentation algorithm uses a quite complex cost function to decide about the creation of a new region. The resulting segmentation is related to a minimum of such cost function. Details about the segmentation algorithm used can be found in [Maio 1996].

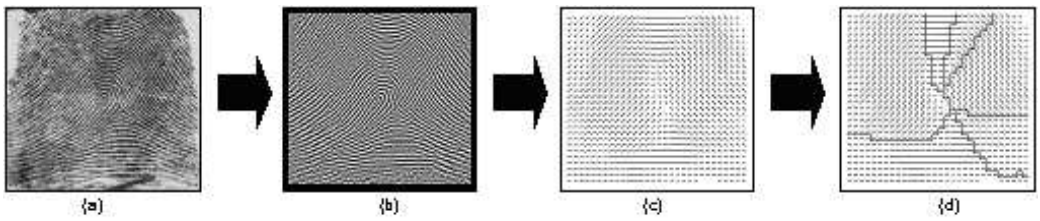


Figure 3.5: Fingerprint image transformation: (a) Original image, (b) Enhanced image, (c) Orientation field from the enhanced image, (d) Segmentation extraction from the fingerprint's orientation field

3.4 A structural-connesionist approach

The proposed approach uses a machine learning architecture explicitly aimed to face on structured data. With regard to such solution, Frasconi (1998) [Frasconi 1998] and Sperduti (1997) [Sperduti 1997] proposed the so called

"Recursive Neural Networks" (RNNs). By using this machine learning architecture, we avoid the problem to design a set of templates for each class, because Recursive Neural Networks are specialised in learning to classify complex data structures by examples.

The main limitation of such approach is that RNNs can learn to classify only data structures in terms of Directed Positinal Acyclic Graphs (DPAGs). A DPAG is a directed acyclic graph in which the "children-nodes" (the nodes linked by another node, also called "father-node") are ordered according to a certain rule. As an example, a node of the DPAG can have the first child, the second child, the fourth child, while the third one is missed. In a DPAG for classification by RNNs, (a) the maximum number of children-nodes, called "out-degree", is given; (b) the "super-source" node is also defined as the node which connects all nodes of the graph, by following a directed path [Frasconi 1998].

It is evident that the use of a DPAG implies some topological constraints which could determine the loss of information in describing the fingerprint structure. In particular, the DPAG could not take into account all segmentation regions because of the designed positional rule between children-nodes and father-node. So, a DPAG generation algorithm could be not able to preserve the original fingerprint segmentation topology. In order to reduce such possible loss of information, a DPAG generation algorithm addressing such issue is needed [Yao 2003]. The DPAG based representation of fingerprints is then completed by attaching to each graph node some local characteristics of regions and some geometrical and spectral relations among adjacent regions.

3.4.1 The directional positional acyclic graph generator module

The main rational behind of our DPAG generation algorithm is

1. to associate a segmentation region to each graph node
2. to draw the completed connected relational graph on the basis of the adjacencies amog regions (i.e. a graph edge connects only adjacent regions)
3. to cut the edges responsible of cycles in the graph on the basis of a hierarchical rule defining the starting node (the super-source), its child nodes and so on.

A rule for ordering the child-nodes is also necessary to obtain a DPAG. In designing such rules, it is necessary to preserve as more as possible the topology of the orientation field segmentation.

The DPAG-based fingerprint description is then completed by attaching to each node a feature vector containing local characteristics of the related region and by geometrical and spectral relations among adjacent regions.
In the following, we describe the algorithm for DPAG generation from the orientation field segmentation and then we describe the features attached to each graph node.

DPAG generation from the orientation field segmentation

It is presented a DPAG generation algorithm from orientation field segmentations in [Yao 2001], [Yao 2003] and [Marcialis 2001], before our generation

algorithm. Briefly, such previous algorithm describes the segmentation topology starting from the region containing the core point. The positional rule between father-node and children-nodes is as follows: 8 positions are considered (8 is the DPAG out-degree), each of them corresponds to the relative location of the child-node with respect to the father-node (North, North-East, East, South-East, South, South-West, West, North-West). Such locations are computed in according to their baricenters relative positions. As an example, if the child-node baricenter is to North of the father-node baricenter, the position "North" is assigned to such child node; when the child node baricenter is to North-East, the position "North-East" is assigned and so on.

The main drawbacks of such algorithm are that:

1. if more than one child-node concur to the same position with respect to the same father-node, some of such nodes could be lost during the DPAG generation, so producing a DPAG generation failure (we called such nodes "orphans-nodes")

2. the core point could not be found at all in certain images, so producing failure in the core detection.

As a consequence of both cases, the fingerprint is rejected because it cannot be make reliable and suitable for the RNN processing. In particular, the first issue indicates that such algorithm is not always able to preserve the original fingerprint topology.

Accordingly, we designed the following algorithm to address such issues. The complete algorithm is presented in the pseudo-code form in Figure 3.6.

Figure 3.7 shows an example of DPAG generation with the proposed algorithm. The proposed algorithm can be summarised as follows:

- ***Input***:
  - **R**={R_1, …, R_M} *is the ordered set* (R_i < R_{i+1}) *of regions of the orientation field segmentation*.
  - *With* <xb_i, yb_i> *we shall denote the x-y coordinates of the* R_i *region's baricenter.*
  - *The order in the set* **R** *is defined as following:*
    R_i < R_j **if** (xb_i<xb_j) **or** ((xb_i==xb_j) **and** (yb_i<yb_j))
  - S *denote the whole orientation field image. This region is the super-source of the DPAG.*
  - Dx *and* Dy *are respectively the orientation field image width and height*
  - od+M *is the max DPAG's outdegree, being* od *its min value*
- ***Output***: **G** = (**N**,**E**), *the DPAG with nodes set* **N** *and edge set* **E**
- *An edge in the DPAG is denoted* (u, v, j) *indicating that* v *is the* j-th *child of* u.

```
N ← {S, R1};
E ← ϕ;
for i ← 1,…,M, do Colour(Ri)← WHITE; HasFather(Ri) ← No;
for i ← 1,…,M do
    Colour(Ri) ← BLACK;
    for j ← 0,…,od-1 do
        rj = the rectangle with vertices : < xbi + j·(Dx+xbi)/od ,0 > and < xbi + (j+1)·(Dx+xbi)/od , Dy >
        R(j) ← { Rh in R: <xbh, ybh> is in rj}; /* Rh < Rh+1 according to the order definition */
             ← False;
        h ← 1;
        while(h<|R(j)| and Assigned=False) do
              Rh ← the h-th region in R(j);
              if (Colour(Rh)=WHITE and Adjacent(Ri,Rh)=true)
              then
                    Assigned ← True;
                    E ← E U {( Ri, Rh, j)};
                    N ← N U {Rh};
                                h) ← Yes;
              h ← h + 1;

E ← E U {( S, R1, 0)}; /*we append the not-linked regions to the super-source*/
  ← od;
for i ← 2,…,M do
   if (HasFather(Ri)=No)
   then
              E ← E U {( S, Ri, j);
              N ← N U {Ri};
                ← j + 1.
```

Figure 3.6: Pseudo-code of the DPAG generation algorithm

- The whole orientation field image is the super-source S
- The regions of the segmented orientation field image are first ordered according to the relative positions of the centre of mass
- The first region R1 is assigned as the first child of the super-source

- The sub-image starting from the x-coordinates of the R1's centre of mass is partitioned in *od* rectangles, where *od* is the out-degree of the DPAG. Figure 3.7 shows an example of such rectangles starting from the region labelled with "0". Figure 3.7 also shows the center of mass of the regions by little filled circles. In the example, $od = 8$

- The first baricenter belonging to an adjacent region of R1, found in the i-th rectangle, is assigned as the i-th child of the node associated to R1

- The same process is repeated for the children-nodes while all regions have been considered

It is easy to see that this process allows to avoid the presence of cycles in the graph. However, it may be happen that a node may be assigned as child of any DPAG's node. In order to take into account these nodes, we simply attached them to the super-source S (the whole orientation field image) by considering them as "super-source children" in the positions $od + 1$, $od + 2$ and so on, according to their order. Consequently, the DPAG out-degree is $od + N$, being N the number of segmentation regions.

The above algorithm does not present the drawbacks of the previous one [Yao 2003] because:

- it avoids the issue of the nodes loss by introducing the ordered rule for recovering the orphans-nodes

- it avoids the dependence of the starting point on the fingerprint core detection

It is also worth noting that the fingerprint topology preserved by the proposed

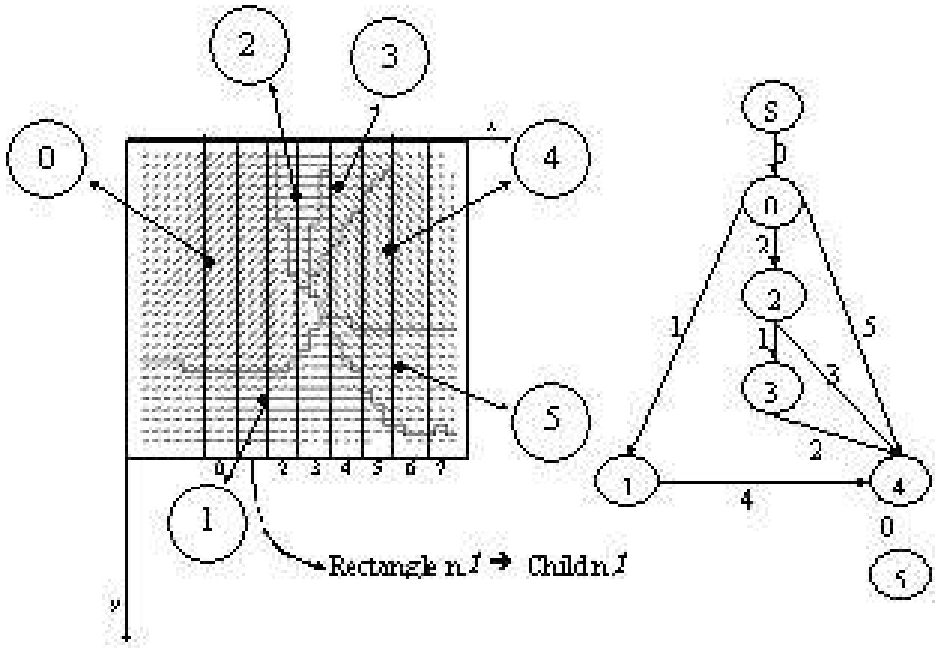


Figure 3.7: Example of DPAG generated from the orientation field image. The out-degree is 8. In this example, the region '0' has the baricenter at the position $\{x = 7, y = 10\}$. According to the algorithm of Figure 8, this is the first child of the super-source S (the whole image). Then, the sub-image starting from the x-coordinate of the baricenter of '0' is partitioned in 8 rectangles labelled from 0 to 7. The baricenter of Region '1' is located in the rectangle no.1. Being Region '1' adjacent to Region '0', Region '1' is assigned as the child no.1 of Region '0', as it can be seen from the label of the related arch of the DPAG

algorithm, because it takes into accunt all regions. So, it is possible to averagely recover the original segmentation topology.

Feature extraction for the DPAG representation

The representation is completed by characterising the nodes with local features and relational features with children-nodes. The first ones are:

- Mean and standard deviation of the region orientations
- Baricenter-coordinates and area of the region. Area's value is normalised with respect to the area of overall image.
- Distribution of the orientation field in the image, in terms of probability of a certain orientation value given the region. Eight orientation values were considered in the range $[j\pi/4, (j+1)\pi/4]$, where $j = 0, \ldots, 7$, and the number of pixels of the orientation field of the region that fall in each interval was computed. In the following, we indicated this number with c_j, related to the j-th interval. For estimating the probability, each value was normalised with respect to the area of the region. Hence, for each region (node):
$$p_j = \frac{c_j}{A}$$
- "Cumulative" distribution of the orientation field. For each node, the following feature is defined: $cum_j(v) = c_j(v) + \sum_{u \in Children(v)} c_j(u)$, where $Children(v)$ is the set of ordered v's children nodes. In the case of a leaf-node: $cum_j(v) = c_j(v)$. The normalisation with respect to the sum of the node areas is performed:
$$p_{cum_j}(v) = \frac{cum_j(v)}{A(v) + \sum_{u \in Children(v)} A(u)}$$

The relational features are "distance" values:

- Among the baricenters
- Among the means and among the standard deviations
- Among the distributions of the orientation field of different regions. Named $d(u, v)$ this distance:

$$d(u, v) = \sum_j |p_j(v) - p_j(u)|$$

where $u \in Children(v)$

- We computed the perimeter of adiacency among two adiacent regions
- We also computed a modified version of the Mahalanobis distance for characterising the relationship among means and standard deviations of different regions. Named μ_f and σ_f the mean and the standard deviation of the orientations of the father-node, and named μ_c and σ_c the mean and the standard deviation of the orientations of the child-node, we defined:

$$d(R_f, R_c) = \frac{(\mu_f - \mu_c)^2}{\sigma_f \sigma_c}$$

3.4.2 Recursive neural networks for fingerprint classfication

Research in connessionist models capable of representing and learning structured (or hierarchically organised) information begun in the early 90's with recursive auto-associative memories (RAAM) [Pollack 1990]. Since then, several other architectures have been proposed, including holografic reduced representation (HRR) [Plate 1995], and Recursive Neural Networks (RNN)

([Goller 1996], [Sperduti 1997], [Frasconi 1998]). A selection of papers in this area appeared in [Frasconi 2001].

Our approach will rely on *Recursive Neural Network*, a machine learning architecture which is capable of learning to classify hierarchical data structures, such as the structural representation of fingerprints which we employ in this chapter. The input to the network is labelled DPAG U, where the label $U(v)$ at each vertex v is a real-valued feature vector associated with a fingerprint region.

A RNN performs a "recursive transduction" that maps a graph V in another graph X_V wich has the same topology. Hence, to each node n_V of V corresponds a node n_{X_V} of X_V. As shown in Figure 3.8, a feature vector $X(n_{X_V}) \in \Re^n$ is associated to each node n_{X_V}, computed on the basis of v's label, according to the formula:

$$X(n_{X_V}) = f(X(u_1), \ldots, X(u_k), U(n_V)), \text{ where } u_j \in Children(n_{X_V}) \quad (3.1)$$

Figure 3.8 depicts that vector $X(n_{X_V})$ contains the distributed representation of the sub-graph dominated by n_{X_V} (i.e., all the nodes that can be reached starting a directed path from n_{X_V}). $X(n_{X_V})$ is called "state vector".

f is called "state transition function". It combines a vector encoding the label of v with the state vectors of $\{u_1, \ldots, u_k\}$, which is the *ordered* set of n_{X_V}'s children. Computation proceeds recursively from the nodes without children to the super-source (the node dominating all other nodes). The base step for Eq. 3.1 is $X(u) = 0$ if u is a missing child.

In our case, the transition function f is computed by a multilayer perceptron (MLP) [Bishop 1995], which is replicated at each node in the DPAG,

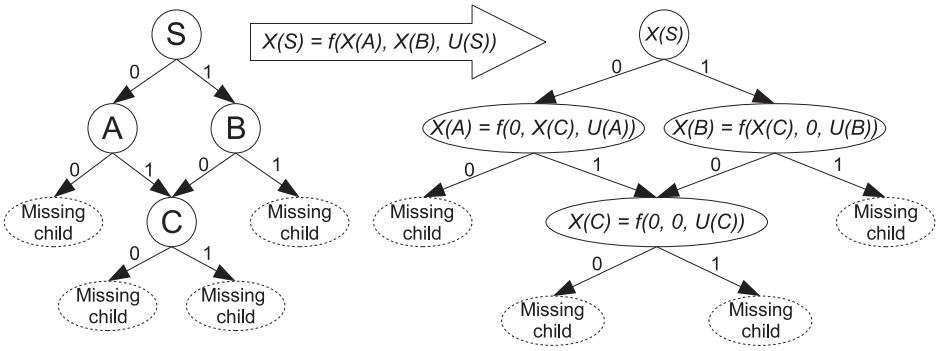


Figure 3.8: A recursive transduction from a simple input DPAG ($outdegree = 2$) to the state-DPAG labelled with state vectors. The node labelled with the state vector $X(S)$ contains the distributed representation of the whole input DPAG. Each child can be univocally identified through its position with respect to the father: e.g., A is the first child of S, B the second. It is worth noting that C has not children. In this case, the base-step is applied for each missing child

sharing weights among replicas. Classification with recurrent neural networks is performed by adding an output function g that takes as input the hidden state vector $X(s)$ associated with the super-source s:

$$Y = g\big(X(s)\big) \tag{3.2}$$

It is worth noting that $X(s)$ can be extracted and independently used as a "structural" feature vector, because it contains the distributed representation of the whole DPAG. Function g is also implemented by a multilayer perceptron.

The output layer in this case uses the *softmax* functions (normalised exponentials), so that Y can be interpreted as a vector of conditional probabilities of classes given the input graph, i.e. $Y_i = P(C = i|V)$, being C a multi-

nomial class variable [Bishop 1995]. Training relies on maximum likelihood. The training set consists of T pairs

$$D = \Big\{\big(U_1, c(U_1)\big), \ldots, \big(U_t, c(U_t)\big), \ldots, \big(U_T, c(U_T)\big)\Big\} \tag{3.3}$$

where $c(U_t)$ denotes the class of the t-th fingerprint in the data set. According to the multinomial model, the log-likelihood has the form:

$$l(D;\Theta) = \sum_t log Y_{c(U_t)} \tag{3.4}$$

where Θ denotes the set of trainable weights and t ranges over training examples. Optimisation is performed with a gradient descent procedure, where gradients are computed by the Back-Propagation Through Structure algorithm [Sperduti 1997].

In order to take into account the cross-referenced fingerprints, characterised by two classes instead of one, a "soft" target vector was introduced in the training phase. The two cross-referenced classes were considered to have the same probability given the pattern. Thus, the target-vector takes value 0.5 in correspondence of the two target classes of the cross-referenced fingerprints. For the standard fingerprints, the target-vector takes value 1.0 in correspondence of the target class.

3.5 The structural K-nn approach

One of the most natural structural representation of the fingerprint orientation field segmentation (i.e., of the segmentation of the fingerprint image in regions with homogeneous orientation of ridge and valley, as shown in Figure 3.2) is a relational graph. Relational graphs appear to be appropriate,

as nodes could naturally correspond to the regions extracted by the segmentation algorithm [Lumini 1999]. Each graph node can be associated to a segmentation region and the edges join two nodes according to the adjacency relationship of the respective regions.

Figure 3.9 shows an example of relational graph related to a fingerprint orientation field segmentation.

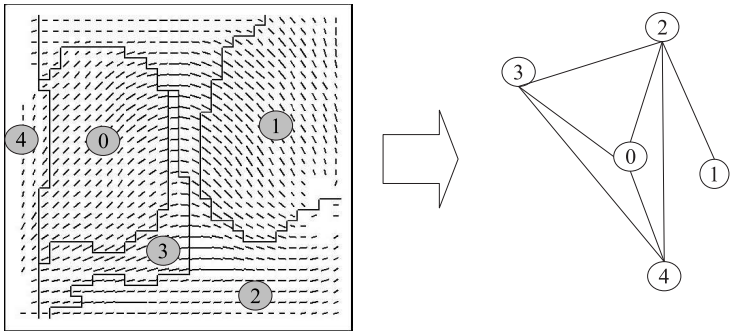


Figure 3.9: Graph-based representation obtained from the segmented orientation field of a fingerprint image. Node labels represent the number associated to each region as shown in the orientation field and the edge labels represent the position of each child-node

The representation is completed by associating to each node a feature vector containing the local characteristics of the regions (area, average directional value, etc) and the geometrical and spectral differences among adjacent regions (relative positions, differences among directional average values, etc). A graphical representation of this kind of graph is shown in Figure 3.10.

Graph matching is a method to perform structural data classification. The graph matching we used is based on the computation of the graph edit distance between the input graph and a set of prototype graphs representing each class. It works such as the K- nearest neighbor classifier but the distance

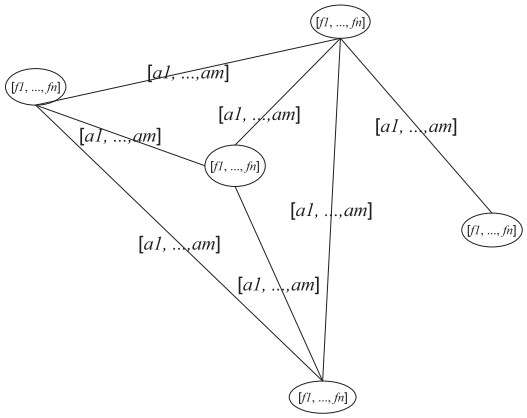


Figure 3.10: A generic attributed graph. Node labels represent the number associated to each region as shown in the orientation field and the edge labels represent the position of each child-node

between input patterns and prototypes, since the patterns are represented by graphs, is the edit distance, that is, a particular measurement of differences between two graphs. Therefore, distances between input graph and model graphs are computed; then, the class associated to the input graph is the most represented in the nearest K prototypes to the input graph.

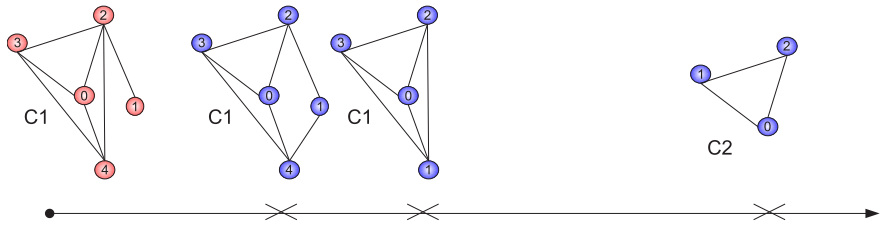


Figure 3.11: K nearest neighbors representation in a space in which can be represented graphs. The distance between graph patterns is edit distance, i.e. a measurement of difference between two graphs

Edit distance is the minimum cost obtainable by applying edit operations, i.e. node/edge substitution, in order to transform an input graph to a

prototype graph. Figure 3.12 shows an example of such transformation.

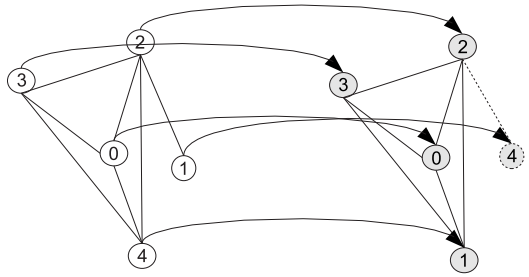


Figure 3.12: An example of transformation from input graph into model graph by edit operations: for all nodes except one a substitution is applied and for one node an insertion is necessary to have the same number of nodes of model graph

A cost is associated to each node operation and the overall cost is the sum of all edit operation costs. The edit operations we used are node and edge insertion, cancellation and substitution. The cost of each operation depends on selected discriminant features and on weights assigned to these features. In order to calculate edit operation costs, a cost function is defined.

$$C_e = \sqrt{\sum_{i=1}^{N_f} \Big(C_i \big(f_i(v) - f_i(w) \big)^2 \Big)} \tag{3.5}$$

Formula 3.5 represents the cost function for a single edit operation. Functions f_i are the discriminant features, selected to define the costs, and their value depends on the current node, if f_i is a node feature, or depends on the current edge, if f_i is an edge feature. The cost function definition is a measurement of the node/edge feature value difference between the node/edge v of the input graph and the node/edge w of the model. In particular, each difference is weighted by the C_i coefficients to give different importance to each feature.

If cancellation or insertion operation is applied, the feature value related to the input graph or to the model graph is zero. Then, getting simpler, the cost function becomes:

$$C_e = \sqrt{\sum_{i=1}^{N_f} \left(C_i f_i^2(v)\right)} \tag{3.6}$$

The main issue is to find the sequence of edit operations which provide the minimum cost. To this aim, a research tree containing all the possible edit operations sequences is constructed. The search of the best sequence (i.e. the minimum cost path into the research tree) is performed by an algorithm similar to A* [Bunke 1983]. This procedure allow to obtain the absolute minimum cost, namely, allow to find the optimal solution of minimum path searching problem. The main drawback of such a search in the tree is the computational complexity in terms of time. Hence, some trick to reduce the time of computing is applied.

Since there is a C_i coefficient for each feature used, in order to avoid to select too many C_i, few features are used, the most significant. In particular, the edit operations cost is based on three node features and only one edge feature. The following list shows the features selected for each edit operation. They are a subset of that used for RNNs described in chapter 3.4.

- Node substitution
  - Area and baricenter coordinates
  - Orientation densities in the 8 main directions
- Node cancellation/insertion
  - Area

- Edge substitution
  - Perimeter of adiacency
- Edge cancellation/insertion
  - Perimeter of adiacency

Note that, to have a distance, cancellation and insertion must produce the same cost, so the related coefficients must be equal. Moreover, edge cancellation may happen in two cases:

1. After node substitution, if doesn't exist the link between the two substituted nodes in the model graph
2. After node cancellation, it is necessary to eliminate all edges arriving in the cancellated node

In order to distinguish these two cases, two different coefficients are used. Obviously, dual consideration is worth also for edge insertion. So we have two other different coefficients for edge insertion too.

In order to have outputs for the combination task with other investigated classifiers, for each test pattern, the mean of K lowest edit distances for each class is computed and then converted into a posterior probabilities vector.

Chapter 4

Ensembles of Graph Matchers and Fusion of Structural and Statistical Fingerprint Classifiers

The aim of this work is to generate Multiple Classifiers System (MCS) using structural methods as individual classifiers of the combination system to classify fingerprints. In particular, we would obtain MCSs automatically from the same type of classifier. In other words, we would generate an *Ensemble of Graph Matchers*. In the literature there are various methods to create MCS when the individual classifiers are statistical type. On the contrary, so far, only few approaches with structural individual classifiers have been proposed (see Section 2.3), and anybody has not yet been proposed an Ensemble of Graph Matchers for fingerprint classification.

First of all, we consider in the section 4.1 the combination with diverse classifiers for fingerprint classification, i.e. statistical one and different structural ones. In the section 4.2, we describe how to perform a Multiple Classifier System for statistical classifiers in order to evaluate either if it is possible to use the same approaches for structural classifiers or if it is possible to adapt them. Then, we describe our approaches to design ensembles of structural matchers.

4.1 Fusion of structural and statistical fingerprint classifiers

In this section, we describe our approach for decision-level fusion of structural and statistical classifiers. The general scheme is reported in figure 4.1, which is quite similar to the commonly used multiple classifiers fusion scheme at the decision-level [Roli 2002].

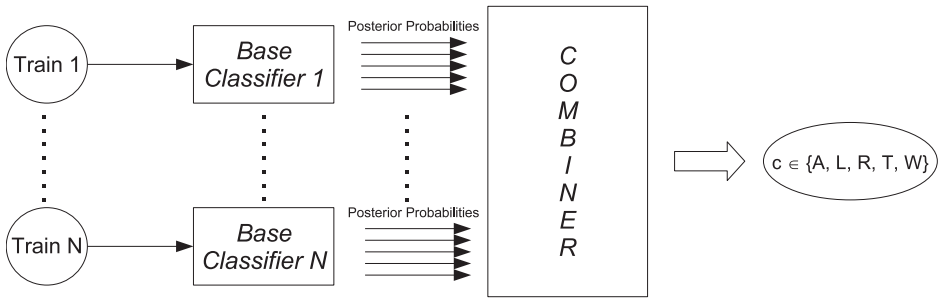


Figure 4.1: General scheme of a fingerprint classification system

We used the finger-code as statistical representation of the fingerprint ([Jain 1999 b]). This vector is the input of a MultyLayer Perceptron trained according to the maximum likelihood cost function. The outputs of the net

have the same meaning than those of Recursive Neural Network, Structural K-nn and Dynamic Masks[1], i.e. the estimation of the conditional probability of each class given the fingerprint pattern with its input features. Hence, the output of each net is a 5-dimensional vector of probabilities. In the following, we denote with p_c^{RNN} and p_c^{MLP} and so on for the other classifiers, the c-th outcome of each classifier, representing the probability of the c-th class, given the pattern ($c \in \{A, L, R, T, W\}$).

Many experimental results heve been shown that classifiers specialised on different pattern representations can benefit from the fusion of their outcomes, especially when this information produces "complementary" classifiers [Roli 2002]. In our case, RNN, MLP Structural K-nn and Dynamic Masks were trained to classify on diverse information. We studied their complementarity in next chapter.

Accordingly, we assessed two types of fusion algorithm (or "combination rules"). The first one was based on a fixed transformation of the outcomes of the experts. In particular, we used the mean and the product rules:

$$winnerClass = argmax_{c\in\{A,L,R,T,W\}} \sum p_c^i \tag{4.1}$$

$$winnerClass = argmax_{c\in\{A,L,R,T,W\}} \prod p_c^i \tag{4.2}$$

where $i \in \{RNN, MLP, SKnn, DMask\}$, i.e. represents one of the individual classifiers and it is possible to have combination either with two, three or all four individual classifiers.

These simple combination rules require the conditional indipendence of the classfiers given the class, and a strong complementarity, to give optimal

[1]In our experiments of system combination we used all these strucutral classifiers, as well as the cited statistical one.

results [Kittler 1998].

The second fusion algorithm followed the so-called "meta-classification" (as well as known as "stacked") approach which uses an additional classifier for combination [Giacinto 1997]. In particular, a K-Nearest Neighbors classifier was used [Duda 2001]. The input of such classifier is a novel feature vector made up of the outcomes of the expert.

4.2 Ensembles of graph matchers

The fusion of classifiers can happen in different points of classification process. Figure 4.2 shows that one can fuse at the level of acquisition module when more than one sensor is utilized. It is the Data Level Fusion. Another possibility is to fuse at the level of features, manipulating them. The Decision Level Fusion performs the combination of the outputs of individual classifiers. At any level the designer wants to work, the aim is to generate complementar classifiers in order that each base-classifier is competent on a feature space portion or, in general, on a particular domain. We focused our attention to the latter level of fusion.

In order to create a multiple classifiers system, different kinds of classifiers can be considered as base classifiers, like proposed in [Serrau 2005] and in [Marcialis 2003] for fingerprint classification. In these works statistical and different types of structural classifiers are combinated at the decision-level fusion. In order to create automatically different classifiers of the same type, that is, to create "Ensembles of classifiers", one can manipulate training data or input and output features.

By manipulating training data, one can create through the bootstrap

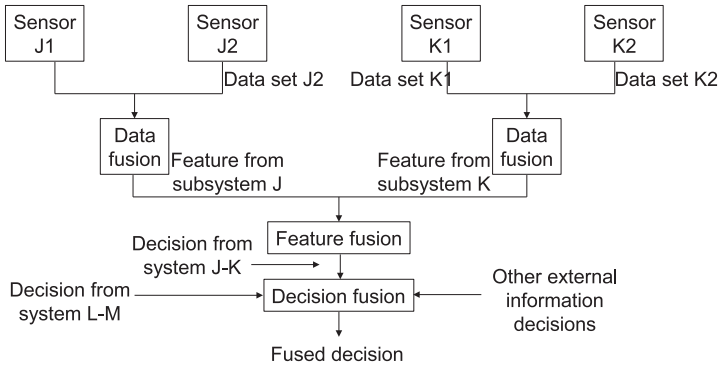


Figure 4.2: Points of the classification process in which it is possible to perform the fusion of more classifiers

technique the so called *Bagging* system [Breiman 1996]. It consists on (i) constructing N different training sets as bootstrap replicas of the original one, (ii) for each training set so generated, learning a kind of classifier (as an example, the classifier could be a decision three or a neural network) and then (iii) combining the outputs of the individual classifiers with some fusion rules, for example with the mean rule.

Another famous MCS generated by manipulating training data is *Boosting* that iteratively trains a classifier by maintaining a set of weights on training samples. Weights are updated at each iteration, placing more weight on misclassified samples and less weight on correctly classified ones. This forces the classifier to focus on hard training samples.

Moreover, other simple methods are data splitting and cross-validation techniques.

Methods based on In/Out features manipulation are:

- Feature manipulation by hand or algorithm
- The Random Subspace Method (RSM)

- Input features can be manipulated by adding noise
- Output features can be manipulated for creating diverse classifiers (ECOC)

Manual or automatic feature selection can be used for creating different classifiers using diverse feature sets. It can work if there are features either redundant or irrilevant. The sets obtained by selecting from the original set, are subset of that.

The most important method to select features, is the Random Subspace Method. It consists on selecting a certain number of subspaces from the original feature space, and training a classifier on each subspace [Ho 1998]. Feature subsets can varying in number and in dimensionality[2].

Adding noise to feature space is used to resolve the small sample size problem that arise when the number of training patterns is smaller than the feature space dimensionality. It is possible to exploit the noise injection into input features for creating ensembles that differ in training sets. Usually the noise distribution is Gaussian, but it can distort data configuration, therefore it is better injecting noise along the direction of the K nearest neighbors of each pattern [Skurichina 2000].

Error Correcting Output Coding is a way to manipulate output features. Each classifier of the multiple system is trained to be competent on a subset of the class set. For example, iteratively partitioning the class set into two subsets, each classifier has to resolve a binary task. Then, a suitable combination method able to recover the original classes is necessary, e.g. a decoding matrix whose rows are the original classes and columns are code-

[2]Dimensionality of subsets is a critical parameter of the RSM

words associated to each class[3].

Finally, one can create multiple classifiers systems by modifying internal parameters of a certain classifier. As an example, when neural network are used, its topology and architecture could be modified changing the number of hidden neurons and/or the number of hidden layers, so generating different classifiers. In the case of graph-based classifiers, it is possible to exploit internal parameters such as that used for definition of the distance between graphs .

4.2.1 Ensembles of statistical vs. structural classifiers

Intuitively, methods that manipulate the training set without operating on the features, could be applied for create structural MCSs identically to statistical ones, namely, either Bagging or Boosting, but data splitting or cross-validation too, if the dataset is enough large. It is not assured that with these methods a structural classifier can build complementar experts, but there isn't any reason that deny it. Therefore, it makes sense trying these methods. In particular, bagging technique works when base classifiers are "instable"[4]. Intuitively, graph-based classifiers are instable, so Bagging should work if it is applied to a structural classifier.

When MCSs are generated on the basis of features changes, e.g. using the Random Subspace Method (RSM), the application to structural classifiers is not trivial. As minimal, it is necessary an extension to treat the feature

[3]In order to have a good ECOC, row and column separation must be satisfied

[4]As Breiman says in [Breiman 1996], a classifier is *instable* if, producing small changes in bootstrap training sets, after learning phase its outputs are very different with respect to that obtained without introducing changes in the original training set.

vectors labels of each node instead of the classical feature vector, which is unique for each pattern. For example, we can simply select a subset of the original node labels, of course, always the same for each node and for each graph (pattern) for consistency reasons. Another way to do an MCS with RSM is proposed by [Schenker 2004]: he and their contributors select feature subsets by randomly removing nodes in each graph. In spite of difficulties to apply this methods, it seems to be interesting to adapt it for structural classifiers.

Noise injection also is not a trivial extension to graph-based approaches. To injecting gaussian noise, it should be applied equally to the features associated to each node and edge in order to avoid data configuration distortion. Moreover, adding noise into the K nearest neighbors direction could be given for each node or edge. Applying this method to create ensembles seems to be too much complicate, compared with the few benefits obtainable for the fingerprint classification task.

As regards the ECOC application, since it involves only the output features fusion, should be used without changes or extensions for structural approaches. Like for statistical classifiers, the critical issue is to find a good coding.

In conclusion, there is much room to research for ensembles of structural classifiers and there are very few works about it. In particular, for fingerprint classification anybody before us has investigated the possibility to expand ensembles to structural or graph-based methods. In this thesys work we investigated two of the above mentioned approaches: bagging and internal parameters variation. We explain these methods in the next section.

4.2.2 Bagging of structural classifiers

As described in section 3.4, the approaches we designed for fingerprint classification are recursive neural network (section 3.4) and structural K nearest neighbors (section 3.5). They could be both used as base classifier of bagging, but for computational complexity reasons, it is not feasible to apply bagging to structural K-nn. In fact, only one learning of graph-based matchers takes busy many hours a modern computer. On the other hand, for bagging it is necessary to use many (theoretically infinite) base classifiers. Therefore, we apply bagging only to recursive neural network.

After learning phase of the individual classifiers is completed, the posterior probability of each expert is used as feature vector to the combination module. Since it is a classification task with five classes, we have a feature vector of five elements for each individual classifier. All these vectors are the input of a combinator that uses the mean rule to give last classification, still by a 5-dimensional feature vector of the posterior probabilities. Figure 4.3 shows the architecture of the multiple classifier system obtained using recursive neural networks as individual classifiers of the bagging approach and combining with the mean rule, that is, by averaging the posterior probabilities of each test pattern.

4.2.3 Ensembles of structural K-nn

Ensembles of structural K nearest neighbors are obtained by changing the cost function definition aimed for the edit distance computation. As shown

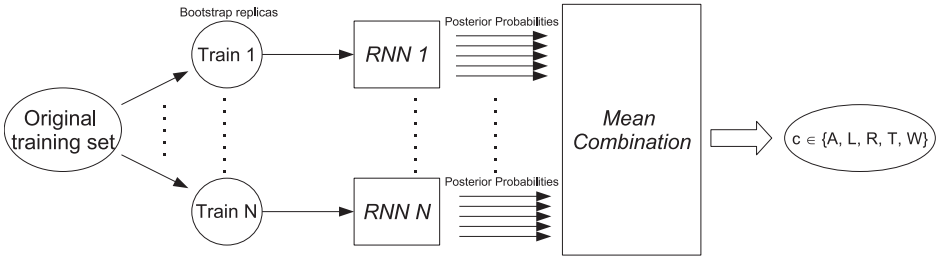


Figure 4.3: Architecture scheme of ensembles of recursive neural networks using bagging

in section 3.5, cost function for a substitution operation is:

$$C_e = \sqrt{\sum_{i=1}^{N_f} \Big(C_i \big(f_i(v) - f_i(w) \big)^2 \Big)} \tag{4.3}$$

while the cost function for either a cancellation or a insertion operation is:

$$C_e = \sqrt{\sum_{i=1}^{N_f} \big(C_i f_i^2(v) \big)} \tag{4.4}$$

We create diverse classifiers by varying, for each learning process, the weights C_i associated to each feature present in the cost function definition. In particular, since the weights C_i are a lot, that associated to the node edit operations are fixed and that associated to the edge edit operations are variable. Altogether, we have three weiths for substitution node operations plus one for cancellation/insertion node operations that are fixed, and one weight for substitution edge operations and two others for cancellation/insertion edge operations[5]. In order to reduce the degrees of freedom, i.e. in order to simplify the problem, the two weights for cancellation/insertion of edges

[5]In this case the weights are two to distinguish the cancellation/insertion of edges due to node substitution from that due to node cancellation/insertion.

are equal. Then, only two weights, that related to edge substitution operations and that related to edge cancellation/insertion operations, can vary to generate different base classifiers.

The architecture of the combination system is similar to bagging with RNNs one. Combination is still performed by mean rule. Figure 4.4 shows this architecture.

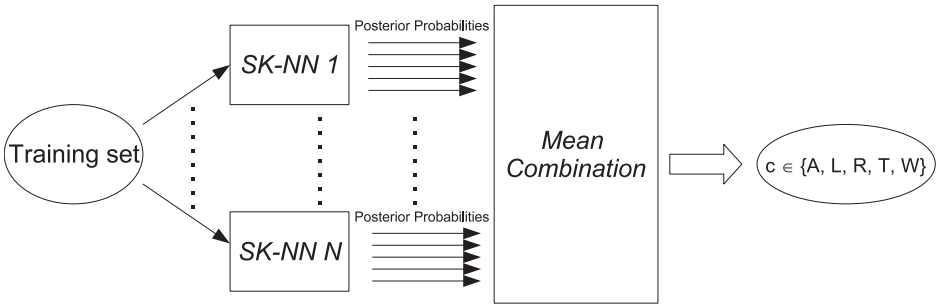


Figure 4.4: Architecture scheme of ensembles of structural K nearest neighbors, generated by varying internal parameters concerning edit distance definition.

Chapter 5

Experimental Investigation

5.1 The data set

The NIST-4 database [Watson 1992], created by the National Institute of Standard and Technology, is a reference data set widely used for assessing and comparing fingerprint classification algorithms. It is made up of 4,000 ink-acquired fingerprint images, equally subdivided in five classes (A, L, R, W, T). Each fingerprint was acquired two times. The first acquisition denotes the fingerprints from f0001 to f2000, the second acquisition denotes the fingerprints from s0001 to s2000. We followed the experimental protocol generally used for such data set (see e.g. [Jain 1999 b, Yao 2003, Senior 2001]). The first 1,800 fingerprints (f0001 through f900 and s0001 through s900) were used for classifier training. The next 200 fingerprints were used as validation set, necessary to perform early stopping of the neural classifiers (RNN and MLP) during the learning phase, and the last 2,000 fingerprints as test set. Seven hundred fingerprint images of NIST4 data set are labelled with two classes instead of only one ("cross-referenced" fingerprints), as they could

not be reliably assigned to a unique class even by human experts. Table 5.1 shows the distribution of the classes in the NIST-4 data set. Rows indicate the first class label, columns indicate the second class label. As an example, the 29,7% of T class fingerprints are "cross-referenced" with the R class. It means that the 29.7% of T class fingerprints are labelled as "TR", class R being the second label for such fingerprints. Values along the diagonal indicate the percentages of fingerprint images labelled with only one class. Typically [Maltoni 2003], cross-referenced fingerprints are considered correctly classified if the classifier assigns them to one of the two classes. Table 5.1 points out that an intrinsic confusion degree characterises the NIST-4 data set. In

	A	**L**	**R**	**T**	**W**
A	95.0	0.0	0.3	4.7	0.0
L	0.0	94.5	0.0	5.2	0.3
R	0.0	0.0	93.3	6.2	0.5
T	18.8	20.7	29.7	30.8	0.0
W	0.0	0.3	0.7	0.0	99.0

Table 5.1: Distribution of the class labels in the NIST-4 Database. Rows indicate the first class label, columns indicate the second class label.

order to use the FingerCode statistical representation [Jain 1999 b], we had to disregard sixty-three fingerprint images due to the impossibility to find the "core" point for such poor quality images. It should be noted that Jain et al. also disregarded such fingerprint images in their experiments [Jain 1999 b].

5.2 Combination of diverse structural classifiers

In this section, we report results on the performance of structural classifiers designed by us (described in chapter3) and of Dynamic Masks devised by Cappelli et al [Cappelli 1999] and described in section 2.2 We firstly compared the performance of structural classifiers, in order to analyse their main pros and cons for fingerprint classification. Then, we investigated their measurement-level fusion according to chapter 4.

5.2.1 Comparison of structural classifiers performance

Table 5.2 reports the class percentage classification accuracies (second to sixth columns) and the overall classification accuracy (seventh column). The second row is related to the dynamic masks method ("DMasks"), the third one to the recursive neural networks-based approach ("RNN"), and the fourth one to the structural K nearest neighbors approach ("SKnn").

	A	**L**	**R**	**T**	**W**	**Overall**
DMasks	48.1	84.5	82.1	66.0	78.4	71.5
RNN	90.7	79.1	83.3	36.2	81.4	76.8
SKnn	71.9	62.3	69.4	52.7	66.3	65.2

Table 5.2: Percentages of the class accuracies and the overall accuracy of the dynamic masks method ("DMasks"), the recursive neural networks ("RNN"), and the structural K nearest neighbors approach ("SKnn").

The best performance is exhibited by the RNN classifier (table 5.2, seventh column). This is mainly due to the fact that RNNs do not need of

class prototypes, because class representations are automatically learnt by examples. Therefore, RNNs are able to better handle the intrinsic small class-separation of fingerprints, which make difficult to find a representative set of class prototypes to use with SKnn. On the other hand, the performance of RNN classifier is the worst on the T class. This is probably due to the massive presence of cross-referenced fingerprints in the NIST4 data set and the introduction of the soft-target, which allowed us to reduce the "noise labelling" effect, but at the expense of the T class training effectiveness, because the T class patterns labelled with only one class are less than the cross-referenced ones (Table 5.1, fifth row).

Although the SKnn classifier performed worse than the RNN on average, their behaviour appears to be similar. Both SKnn and RNN performed well for the A class, and exhibited the worst performance for the T class of fingerprints. The good performance on the A class confirms that structural features could be useful to distinguish strongly structured classes. Accordingly, it can be hypothesized that the performance of the SKnn approach could be strongly improved if a more robust orientation field segmentation algorithm could be designed, or if effective methods for class prototypes selection would be available. In fact, although we used the sophisticated fingerprint segmentation algorithm described in [Maio 1996], segmentations of L, R, and T class fingerprints often contains errors that make the related graphs very similar. This issue clearly demand for future work on graph representation and matching techniques that can handle such segmentation errors.

The dynamic masks classifier performed quite differently with respect to the others. In particular, the performance on the A class is very low.

In our opinion, such a low performance can be explained with the absence of singularity points in the A class, which make quite difficult to design an appropriate dynamic mask for that class. With regard to this issue, it should be noted that the performance on the other classes, which exhibit at least two singularities, is definitely higher.

5.2.2 Decision-level fusion of structural classifiers

First of all, the complementarity among the investigated structural classifiers was investigated using the so called "oracle", that is, the "ideal" combiner able to select the classifier, if any, that correctly classifies the input pattern. It should be noted that the oracle accuracy is usually a very optimistic estimate of the performance achievable with classifier fusion rules. This is due to the fact that the oracle give an estimation of the intersection degree among the sets of misclassified patterns of the individual classifiers, without taking into account the values of posterior probabilities output by them. In order to overcome this limitation, we coupled the oracle results with the analysis of the correlation coefficient among the outputs of each couple of the investigated classifiers.

The performance of the oracle is shown in table 5.3.

The first column shows the "fused" classifiers (the percentage accuracy of the best individual classifier is reported in brackets), the second column shows the performance of the related oracle. Table 5.3 points out that dynamic masks and the other structural classifiers exhibit a certain complementarity degree (second and third rows). It is also worth noting that the highest classification rate can be potentially achieved by combining all three

FUSION of	Oracle
DMasks-RNN (76.8)	91.1
DMasks-SKnn (71.5)	89.2
RNN-SKnn (76.8)	86.1
DMasks-RNN-SKnn (76.8)	94.1

Table 5.3: Performance of the oracle. Accuracy of the best classifier in each combination is reported in brackets

investigated structural classifiers. This means that each classifier can significantly contribute to the performance improvement. However, Table 5.4 shows that the correlation coefficient among their outputs per class is averagely high, except for the couple RNN-DMasks and SKnn-DMasks on A and T classes. These values could be expected because all methods are aimed to describe the same data, i.e. the orientation field segmentation, and also they use similar structural representations. Accordingly, it could be difficult to exploiting the complementarity among these classifiers.

	Class A	Class L	Class R	Class T	Class W
SKnn+DMasks	0.35	0.55	0.58	0.24	0.59
SKnn+RNN	0.81	0.59	0.66	0.46	0.63
DMasks+RNN	0.40	0.67	0.69	0.40	0.70

Table 5.4: Correlation coefficient computed among the individual classifiers. For each classifiers pair, the correlation among class posterior probabilities vectors of a test pattern is determined. Then, the mean for class is calculated.

Table 5.5 shows the performance of individual classifiers and their related decision-level fusion with different combination rules.

The best performance is achieved by the fusion rules based on the KNN

FUSION of	Mean	Product	KNN
DMasks-RNN (76.8)	80.6	79.2	81.7
DMasks-SKnn (71.5)	79.1	77.8	79.8
RNN-SKnn (76.8)	76.1	76.7	76.6
DMasks-RNN-SKnn (76.8)	82.4	82.2	83.6

Table 5.5: Percentage accuracy of the measurement-level fusion of the investigated structural classifiers by the mean rule, the product rule, multi-layer perceptron (MLP) and K-nearest neighbour (KNN). The overall accuracy of the best individual classifier is reported in brackets in the first column

when all the three structural classifiers are combined. But the simple mean rule also gives a good performance (table 5.5, fifth row). This result points out that the contribution of structural K nearest neighbors classifier is difficult to exploit, probably because of the low performance of this approach. On the other hand, reported results points out the high complementarity between the dynamic masks and RNN classifiers. The improvement of the classification performance is about 7% and, according to the oracle results, there is still room for further improvements (table 5.3, tab:structFus, fifth row).

5.3 Comparison and combinations between structural and statistical classifiers

5.3.1 Comparison among statistical and structural approaches

Table 5.6 reports the accuracy on the test set of the statistical classifier mentioned in Section 2.1, that is, the multi-layer perceptron using FingerCodes. First of all, Table 5.6 shows that the overall accuracy of the statistical classifier is higher than the one of any structural classifiers and their combination. However, it is evident from tables 5.2 and 5.6 that, for the A class, the structural classifiers perform definitely better than the statistical one (except for the dynamic masks method).

	Class A	**Class L**	**Class R**	**Class T**	**Class W**	**Overall**
Statistical classifier	80.5	91.8	89.5	79.1	89.4	86.0

Table 5.6: Percentage class accuracies and overall accuracy of multi-layer perceptron trained with FingerCodes on NIST-4 test set

In order to investigate the advantages of structural approaches for discriminating classes with a clear structure, for which standard statistical classifiers often perform not well, we analysed in detail the confusion degree between the A and T classes. Table 5.7 shows the confusion degree between the A and T classes (i.e., the percentage of fingerprints of the A class misclassified as T class fingerprints) of the individual structural classifiers, their best fusion, and the statistical classifier. It should be noted that the confusion among such classes is a well-known issue for the state-of-the-art statistical

classifiers. Table 5.7 shows that structural approaches can be useful to recognize strongly structured fingerprint classes, such as the A class. Even for the dynamic masks and the SKnn classifiers, which do not outperform the statistical classifier individually, Table 5.7 shows that their fusion definitely improve the performance.

Classifiers	A - T confusion degree
DMasks	19.8
RNN	2.7
SKnn	19.4
Best fusion DMasks-RNN	4.5
Best fusion DMasks-SKnn	5.0
Best fusion RNN-SKnn	2.9
Best fusion DMasks-RNN-SKnn	5.2
Statistical classifier	16.7

Table 5.7: Percentage of A-T classes confusion degree of the individual classifiers (masks, RNN, SKnn), their best fusion, and the statistical classifier. The best fusion has been reported according to the best overall accuracy showed in table 5.5

5.3.2 Fusion of statistical and structural approaches

Table 5.8 reports the overall accuracy obtained by using the oracle and the product, mean and KNN fusion rules (third, fourth, fifth and sixth columns, respectively). We also reported the correlation coefficient of the maximum posterior probabilities output by each statistical-structural classifiers couple in the second column. These values, coupled with the oracle performance, points out the strong complementarity between structural and statistical

approaches. In particular, the overall accuracy of the oracle reaches a value near to the 100.0% in the case of the fusion of all classifiers. The other columns shows that this complementarity can be exploited by the fusion rules.

Fusion of	**Corr. Coeff.**	**Oracle**	**Mean**	**Product**	**KNN**
Statistical-DMasks	0.30	93.0	84.4	83.5	86.2
Statistical-RNN	0.26	94.0	87.6	87.8	88.5
Statistical-SKnn	0.23	93.1	86.7	87.0	88.6
Ststistical-RNN-SKnn	-	95.5	86.0	87.5	89.0
Statistical-DMasks-SKnn	-	96.1	86.8	85.8	88.0
Statistical-DMasks-RNN	-	96.5	88.2	85.8	88.8
Statistical-DMasks-RNN-SKnn	-	97.2	88.6	87.0	89.6

Table 5.8: Percentage accuracy on overall of the oracle and the investigated fusion rules. The correlation coefficient of each statistical-structural classifiers couple is reported in the second column.

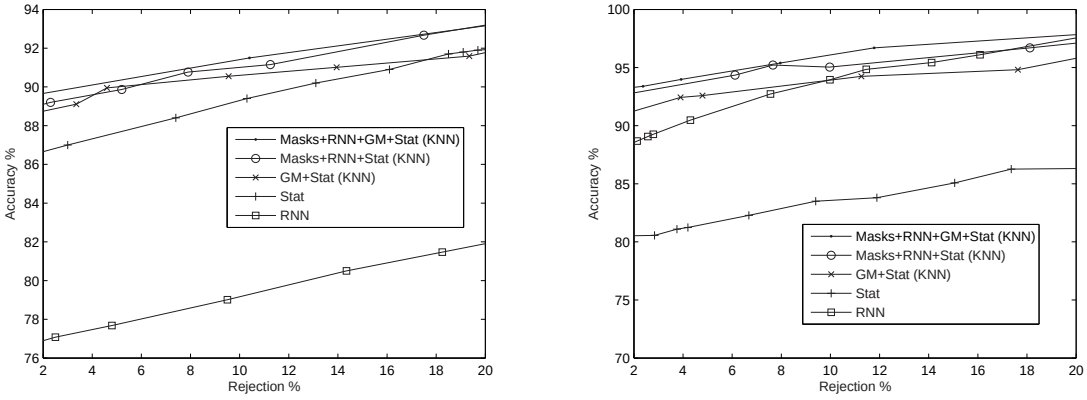
In particular, the good results of mean and product rules, which are simpler than the KNN one, can be explained with the help of Table 5.9. This table reports the mean of the posterior probability of each class for the investigated structural and statistical classifiers. It shows that the outputs of the statistical classifier are averagely higher than those of the structural approaches, except for the DMasks classifier. This means that it is very difficult to change the decisions of the statistical classifier. On the other hand, structural K nearest neighbors and rnn classifiers exhibit a lower value, especially for those classes they are not effective (L, R, T classes). This means that, in many cases, their decision could be 'corrected' by a classifier which exhibit a 'stronger' behaviour, namely, the statistical one. The same

observation can be made for the A class, where SKnn and RNN outperform the statistical classifier. Their posterior probabilities on this class exhibit a value higher than that of the statistical one. Accordingly, many wrong decisions of the statistical approach on this class could be recovered (i.e., can be turned on right decisions) by the fusion with structural ones. In fact, as the fusion by K-nn metaclassifier shows, better performance are achieved when statistical classifier is combined with RNN or SKnn classifier, in spite of the low overall accuracy of the last one.

	Class A	**Class L**	**Class R**	**Class T**	**Class W**
SKnn	0.78	0.54	0.60	0.23	0.57
RNN	0.73	0.61	0.65	0.27	0.78
DMasks	0.43	0.80	0.76	0.40	0.76
Statistical	0.69	0.85	0.82	0.60	0.87

Table 5.9: Mean of class posterior probabilities for each class, for individual classifiers on the test set

Figure 5.1 shows the accuracy-rejection curves of the best classifiers and fusion approaches we investigated. The rejection option makes sense when a fingerprint cannot be classified without a large margin of uncertainty, so increasing the probability of wrong classification, and, consequently, increasing the identification time. In this case, it can be better: (i) to leave the decision to a human expert, or (ii) to submit the fingerprint to a specialised classification module, if any, or (iii) to associate the fingerprint to the couple of most probable classes (and doing a search in the data base limited to such classes). The use of the rejection option obviously increases the final identification time (Section 1). Therefore, a good trade-off between the percentage



(a) (b)

Figure 5.1: The accuracy-rejection curves of the best classifiers and their best fusion algorithm. Graphic 5.1(a) shows the overall accuracy, whereas graphic 5.1(b) shows the accuracy of A class.

of rejected fingerprints and the required classification accuracy is needed. As the FBI requirements for the NIST data bases are 99% of classification accuracy with 20% rejection rate [Maltoni 2003, Karu 1996, Senior 2001], we investigated accuracy for rejection rates ranging from 2% to 20% in our experiments.

We followed the Chow's rule for rejecting the pattern [Chow 1970], that is, its maximum posterior probability should exceed a certain rejection threshold otherwise it is considered as "'rejected"' or not classified. From Figure 5.1, it is evident that, by increasing the number of structural classifiers, it is possible to gradually improve the performance and also to obtain a better classification accuracy when the rejection rate increases, especially for class A accuracy. This confirms that each classifier contributed to the per-

formance improvement significantly, and also impacts on the reliablity of the classification system.

5.4 Bagging with recursive neural networks

In this section, results on the performance of ensemble of recursive neural networks generated using bagging approach is reported. As shown in section 4.2, *Bagging* is a typical method used for generating a multiple classifier system, automatically from the same kind of base classifier. The diversity of individual classifiers in the combination system is due by generating N different bootstrap replicas of the original training set. It is well known ([Breiman 1996] that the number of training replicas must be infinite, that is, N must be enough great to be considered infinite. How much great should be N, dipendes on the particular application and it is not simple to find its value. A typical solution is to learn many individual classifiers and to stop the addition of classifiers in the combination system when the so called "plateau" is found in the graphic representing the behaviour of combination accuracy with respect to the number of individual classifiers. In this case, i.e. recursive neural networks as base classifiers for fingerprint classification on NIST4 database, it is chosen $N = 100$. Then, in order to combine the base classifier outputs, mean rule is used. Figure 5.2 shows the behaviour of bagging accuracy with respect to the N values.

The curve displais that the plateau is reached when about 30 base classifiers are combined and the accuracy is approximately 76.6%. Since the overall accuracy of a single recursive neural network, learned without using bagging, is 76.8%, it is worth noting that bagging doesn't improve performance of a

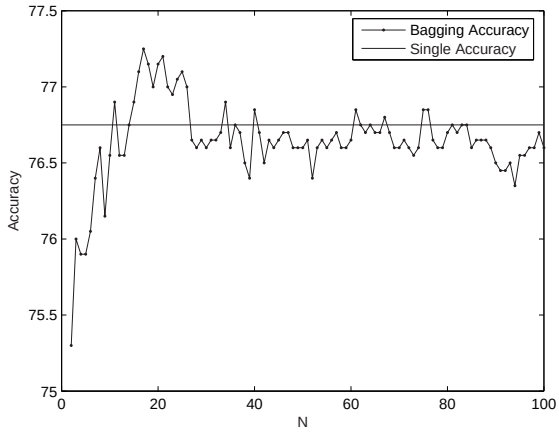


Figure 5.2: Behaviour of bagging accuracy on the test set of NIST4 database with respect to N. Base classifiers are recursive neural networks.

single recursive neural network.

As one could to expect, accuracy of base classifiers is a little worst with respect to that of a single RNN; this fact is due to the instability introduced by bootstrap technique. As the figure shows, the combination of base classifiers improve with respect to them. In conclusion, seems that bagging doesn't work better than the single recursive neural network for fingerprint classification.

5.5 Ensembles of structural K-nn

In this section, we report performance results of *Ensembles of graph matchers*, where graph matchers are structural K nearest neighbors described in section 4.2.

As the computational complexity is too much and the learning process of each individual classifier in the combination system is very time consuming,

it is not feasible to experiment it with all NIST4 dataset we used for the other multiple classifier system, as described in sections 5.2 and 5.3.

Only one individual classifier is learned on all NIST4 dataset and its performance are shown in table 5.2, fourth row. The overall accuracy reported in this table is 65.2% and the classes accuracy is similar to that of recursive neural network, i.e. the A class accuracy is very high with respect to the overall accuracy, while other classes don't achieve good performance, mostly the T class. In our opinion, this similar behaviour is due to the fact that the same image representation (i.e. the orientation field) and the same features are used for both approaches.

In order to demonstrate the effectiveness of this method, aimed to create ensembles of graph matchers in spite of computational difficulties, a reduced set of 200 elements for the training set and other 200 elements for the test set is extracted to NIST4 database; in order to respect the prior probabilities of each class, patterns are randomly selected for the original dataset, that is, the prior probabilities are all the same for each class with respect to the first label of each pattern.

Table 5.10 shows accuracies on the test set of individual classifiers, generated by varying cost function of edit distance in the structural K nearest neighbors. Each row represents a classifier. First and second columns are edit operation weights that characterize differences of each classifier. As said in section 4.2, only weights of edge edit operations vary to generate diverse classifiers.

It is worth noting that performance of individual classifiers are not so different. But combination of some of these classifiers, as shown in table 5.11,

C1	C2	Overall accuracy
15	5	62,00
3	1	58,50
10	1	57,50
15	3	57,50
15	1	57,50
20	2	56,00
30	3	58,00
17	4	62,50
16	2	58,50
17	1	58,00
10	5	60,50
15	5	62,00
10	8	62,00
10	1	61,50
5	1	62,50

Table 5.10: Accuracy of individual classifiers, generated by varying cost function of edit distance in the structural K nearest neighbors. Each row represents a classifier. First and second columns are edit operation weights that characterize differences of each classifier.

improves performance of the best individual classifier. For the combination phase, classifiers are selected on the basis of a validation set.

Each row is referred to a multiple classifier system. Each column, except last one, indicates the overall accuracy of individual classifier, while last column indicates the overall accuracy of multiple classifier system obtained fusing the classifiers of the same row. It is worth noting that, by increasing the number of individual classifiers, combination system doesn't improve its

(a)

S1	S2	Fusione
60.5	61.5	65.5
60.5	62.5	67.0
62.0	60.5	64.5
57.5	60.5	63.5

(b)

S1	S2	S3	Fusione
62.5	60.5	62.5	67.0
62.5	60.5	58.5	65.5
57.5	57.5	57.5	62.0
57.5	60.5	62.5	63.5

(c)

S1	S2	S3	S4	S5	S6	Fusione
57.5	62.0	62.5	62.5	60.5	62.0	64.0
57.5	57.5	62.0	62.5	62.5	60.5	65.0

Table 5.11: Overall accuracies of ensembles of graph matchers fused by mean rule. Combination architecture has of 3, 4 and 6 base classifiers, generated by varying cost function of edit distance in the structural K nearest neighbors.

performance. In particular, the best combination is obtained both with the two individual classifiers related to third row in the table 5.11(a) and with three individual classifiers related to second row in the table 5.11(b).

Table 5.12 shows performance of individual classifiers (second and third row) and related combination of the best fusion of ensembles of graph matchers (fourth row) in terms of class accuracies.

It is worth noting that the behaviour of individual classifiers is similar: very high percentage of correct classified patterns for the A class and worst performance for T and W classes. The A class classification improvement of

	Class A	Class L	Class R	Class T	Class W	Overall
Expert 1	70.45	73.81	57.89	58.06	51.11	62.50
Expert 2	72.09	69.05	48.72	58.06	53.33	60.50
Fusion	93.02	69.05	53.85	38.71	71.11	67.00

Table 5.12: Percentages of the class accuracies and the overall accuracy of individual classifiers and related combination of the best fusion of ensembles of graph matchers.

the combination is more than 20% with respect to the best A class accuracy of single classifiers. Hence, A class accuracy becomes comparable with the A class accuracy of diverse classifiers combination, namely, all structural and statistical shown in section 5.3.2 (in particular, see figure 5.1(b)). Moreover, also W class accuracy improves approximately of 20% with respect to W class accuracies of single classifiers. Unfortunately, T class accuracy deteriorates its performance.

Chapter 6

Conclusions

6.1 Conclusions on diverse classifiers fusion

In chapters 3 and 4 the structural approaches and its combination with the statistical one were investigated. The aim of our study was:

1. to show the classes for which the structural approaches could be effective
2. to investigate the theoretical potentialities of structural-statistical fusion
3. to investigate some fusion rules for exploiting such potentialities

We firstly trained and tested a recursive neural network for distinguishing among fingerprints represented by a DPAG, a graph describing the fingerprint structure. The proposed structural approach presented important modifications with respect to that proposed in previous works: we avoided the DPAG generation dependence on the singularity points, which cannot be easily detected in many computed fingerprint images; we reduced the noise labelling

introduced by the ambiguous fingeprints by using a soft-target during the RNN training.

Then, we trained and tested a structural K nearest neighbors for distinguishing among fingerprints represented by a relational graph describing the fingerprint structure in a different way with respect to that of DPAG for recursive neural networks. This proposed method is a tipical way for classifing structural patterns, but it is the first time that it is applied to fingerprint classification.

We combine these approaches and another relevant structural approach reported in the literature, the dynamic masks approach, themselves and compared their results with that of statistical classifier based on FingerCode. Experimental results appear to confirm that structural approaches can perform better than statistical ones for the strongly structured fingerprint classes, such as the A class. Moreover, their fusion can help in improving classification performances and, in particular, to reduce the problem of A-T classes confusion degree, which is a well- known issue for currently used statistical classifiers. Although definitive conclusions cannot be drawn on the basis of the above limited set of experiments, we believe that this work can contribute to start the discussion about advantages and drawbacks of structural methods for fingerprint classification, and also to indicate some aspects worthy of further investigations.

We combined the structural approaches results with those of a statistical approach based on the FingerCode. Reported results pointed out that structural approaches can distinguish the A class much better than the statistical one. On the other hand, the structural approaches are not sufficient

to achieve good classification performance on the other classes.

Then, we studied the complementarity among structural and statistical approaches. The "oracle" and the correlation coefficient of their outputs used to this aim pointed out the strong complementarity among the above approaches. In particular, the role of each approach to perfomance improvement is quite different, being the structural aprroaches specialised on the A class and the statistical one on the other classes.

Accordingly, we applied different fusion rules to exploit such complementarity: the fixed rules (non parametrical rules, so defining a simple fusion architecture) and the so called meta-classification approach (a K nearest neighbors, so defining a more complex fusion architecture). Reported results on fusion of structural and statistical approaches definitely showed the improvement of the performance with respect to that of the best individual one. A sharp classification performance increase has been pointed out both from fixed rules and meta-classifier. This result pointed out that such complementarity exploitation does not often require very complex fusion architectures. As an example, the mean rule exhibited a classification accuracy superior than that presented by the KNN architecture on the W class; in other cases, performance of fusion by KNN and the fixed rules were comparable. As expected, a powerful fusion rule, as the KNN metaclassifier, has been able to better approximate the oracle behaviour, by working as a "selector" among the structural classifiers and the statistical one for each pattern class.

The complementarity esploitation of the decision-level structural-statistical fusion has been confirmed by the recover rate analysis of all fusion rules. In

particular, the investigated fusion rules exhibited a high capability of recovering patterns wrongly classified by structural approaches. Many A class pattern wrongly classified by the statistical approach have been recovered by our fusion rules too.

Finally, as the accuracy-rejection trade-off is an important issue for a real automatic fingerprint classification systems, reported accuracy-rejection curves analysis based on the Chow's theory pointed out that decision-level fusion is more effective than the best individual approach (the statistical one for the L-R-T-W classes, the structural ones for the A class) in improving the overall performance when ambiguous fingerprint cannot be reliably classified.

Firstly, none of the few works investigating the structural fingerprint classification experimentally analysed the fingerprint classes for which a structural approach is useful. On the contrary, in this work, we clearly showed the crucial role that the proposed structural approaches play in fingerprint classification. Accordingly, the interest in structural fingerprint classification should be renewed: other structural approaches could be analysed and their fusion with other statistical approaches could be investigated to obtain more general results than ours. Secondly, very few works about decision-level structural-statistical fusion have been proposed so far. However, the high potentiality of such fusion, which we showed in this work using different fusion rules, should contribute to stimulate the interest around such challenging topic. In particular, the design of decision-level fusion rules explicitly aimed to exploit the structural-statistical complementarity is still an open issue.

6.2 Conclusions on ensembles of graph matchers

Once designed the individual classifiers (recursive neural network and structural K nearest neighbors), they are adapted to generate ensembles, that is, a lot of individual classifiers of the same type trained with some different characteristic about internal parameters, input features or output features.

We trained and tested two kind of ensembles, the first regarding recursive neural network with differences in input features, the latter regarding structural K nearest neighbors with differences in internal parameters.

Ensembles of recursive neural networks, generated using bagging procedure, have performance similar that obtained with a single recursive neural network. Performance of the individual RNNs trained with bagging, are lower than a single RNN trained without bagging perturbation. With respect to base classifiers performance, ensembles improve their accuracy. Hence, although the overall accuracy for fingerprint classification on NIST4 is not better than the single classifier one, ensemble created by bagging works well, like for statistical base classifiers.

Ensembles of structural K nearest neighbors are trained and tested on a reduced dataset for computational complexity reasons. Base classifiers so generated are weak classifiers and their performance are similar. Combination of some base classifiers outperforms with respect to the best individual classifier. By increasing the number of individual classifiers, combination system doesn't improve its performance. It is probably due to the fact that base classifiers have similar behaviour, hence few classifiers have a high com-

plementarity with respect to the others. Regarding the single class accuracies, the behaviour of individual classifiers is similar: very high percentage of correct classified patterns for the A class and worst performance for T and W classes. The A class classification improvement of the combination is more than 20% with respect to the best A class accuracy of single classifiers. Moreover, also W class accuracy improves approximately of 20% with respect to W class accuracies of single classifiers. Unfortunately, T class accuracy deteriorates its performance.

Another time we found the most relevant result: structural classifiers, either single or combined, are very usefull to distinguish the strong structured classes, such as the A class for fingerprint classification. Like for diverse structural-statistical combination, for ensembles of structural matchers too, none of the few works investigating the structural fingerprint classification experimentally analysed the fingerprint classes for which a structural approach is useful. On the contrary, in this work, we clearly showed the crucial role that the proposed structural approaches play in fingerprint classification. Accordingly, the interest in structural fingerprint classification should be renewed: other approaches of ensembles of structural classifiers could be analysed and investigated to obtain more general results than ours. Secondly, very few works about ensembles of graph matchers have been proposed so far, especially for fingerprint classification. However, the high potentiality of such fusion, should contribute to stimulate the interest around such challenging topic. In particular, the design of other multiple classifiers systems using graph-based approaches explicitly aimed to exploit the base classifiers complementarity is still an open issue, which will be the subject of our future

works.

Bibliography

[Jain 1999] A.A.V.V. "Biometrics - Personal Identification in Networked Society", edited by Anil Jain, Ruud Bolle e Sharath Pankanti - Kluwer Academic Publisher, Boston/Dordrecht/London, 1999

[Wechsler 1997] Wechsler H., Phillips J.P., Bruce V., Folgeman Soulie F., Huang T.S.(Eds.), 1997 "Face Recognition" - From theory to applications. Springer, ASI NATO Series, vol. 163

[Daugman 1993] Daugman J.G. 1993 "High Confidence Visual Recognition of Persons by a Test of Statistical Independence" IEEE TRansactions on Pattern Analysis and Machine Intelligence, 15 (11) 1148-1161

[Furui 1997] S. Furui, "Recent advances in speaker recognition", ni Lectures Notes in Computer Scienze 1206, Proceedings of Audio - and Video Biometric Person Authentication AVBPA '97, First International Conference, Crans-Montana, Switzerland, March 12-14 pp. 237-252, Springer-Verlag, Berlin, 1997

[Prokoski 1992] F.J. Prokoski, R.B. Riedel, J.S. Coffin, "Identification of individuals by means of facial thermography", in Proceedings of The IEEE 1992 International Carnahan Conference on Security Technology: Crime

Countermeasures, Atlanta, GA, USA 14-16 Oct., pp. 120-125, IEEE, 1992

[Hill 1978] R.B. Hill, "Apparatus and method for identifying individuals through their retinal vasculature patterns", US Patent No. 4109237, 1978

[Zhang 2003] Zhang D., Kong W.K., You J., Wong M., 2003 "Online Palmprint Verification" IEEE Transactions on Pattern Recognition and Machine Intelligence 25 (9) 1041-1049

[Kumar 2003] Kumar A., Wong D.C.M., Shen H.C., Jain A.K., 2003 "Personal Verification using Palmprint and Hand Geometry Biometric" Proc. 4th Int. Conf. on Audio- and Video- Based Person Authentication AVBPA 2003, J. Kittler and M.S. Nixon Eds., Springer LNCS 2688, pp. 668-678

[Herkel 2003] C. Herkel, H. Bunke, 2003 "A set of novel features for writer identification" Proc. of the 4th Int. Conf. on Audio- Based Person Authentication AVBPA 2003, J. Kittler and M.S. Nixon Eds., Springer LNCS 2688, pp. 679-687

[Kale 2003] A. Kale, N. Cuntoor, B. Yegnanarayana, A.N. Rajagopalan, R. Chellappa, 2003 "Gait analysis for human identification" Proc. of the 4th Int. Conf. on Audio- Based Person Authentication AVBPA 2003, J. Kittler and M.S. Nixon Eds., Springer LNCS 2688, pp. 706-714

[Mansfield 2002] A.J. Mansfield, J. Wayman, 2002 "Best practices in testing and reporting performance of biometric device" NLP Report CMSC 14/02

[Maltoni 2003] D. Maltoni, D. Maio, A.K. Jain, and S. Prabhakar, Handbook of Fingerprint Recognition, Springer Verlag, 2003

[Henry 1900] E.R. Henry, Classification and Uses of Fingerprints, Routledge, London, 1900

[Pankanti 2002] S. Pankanti, S. Prabhakar, A.K. Jain, 2002 "On the individuality of fingerprints" IEEE Transactions on Pattern and Machine Intelligence, 24 (8) 1010-1025

[Bolle 2002] R.M. Bolle, J.H. Connell, N.K. Ratha, 2002 "Biometric perils and patches" Pattern Recognition, 35 (12) 2727-2738

[Karu 1996] K. Karu and A.K. Jain, Fingerprint Classification, Pattern Recognition, 29 (3) 389-404, 1996

[Lee 1994] H.C. Lee, R.E. Gaensslen (eds.) "Advances in fingerprint technology" CRC Press, 1994

[Ghong 1997] M. Chong et al., " Geometric Framework for Fingerprint Image Classification", Pattern Recognition, vol. 30, no. 9, pp. 1475-1488, 1997

[Duda 2001] R. Duda, P. Hart, and D. Stork, Pattern Classification - Second Edition, John Wiley & Sons, 2001

[Candela 1995] G.T. Candela, P.J. Grother, C.I. Watson, R.A. Wilkinson, and C.L. Wilson, PCASYS - A Pattern-Level Classification Automation System for Fingerprints, NIST tech. Report NISTIR 5647, 1995

[Jain 1999 b] A. K. Jain, S. Prabhakar, L. Hong, "A Multichannel Approach to Fingerprintf Classification", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 21, no. 4, pp.348-358, 1999

[Cappelli 1999] R. Cappelli, D. Maio, and D. Maltoni, Fingerprint classification based on Multi-space KL, Proc. AutoID'99, Summit, NI, pp.117-120, 1999

[Nagaty 2001] K.A. Nagaty, Fingerprint classification using Artificial Neural Networks: a combined structural and statistical approach, Neural Networks, 14 (9) 1293-1305, 2001

[Yao 2003] Y. Yao, G.L. Marcialis, M. Pontil, P. Frasconi, and F. Roli, Combining Flat and Structural Representations for Fingerprint Classification with Recursive Neural Networks and Support Vector Machines, Pattern Recognition, 36 (2) 397-406, 2003

[Moayer 1975] B. Moayer and K.S. Fu, A syntactic approach to fingerprint pattern recognition, Pattern Recognition, 7, 1-23, 1975

[Rao 1980] K. Rao and K. Balck, Type Classification of Fingerprints: a Syntactic Approach, IEEE Transactions on Pattern Analysis and Machine Intelligence, 2 (3) 223-231, 1980

[Lumini 1999] A. Lumini, D. Maio, and D. Maltoni, Inexact graph matching for Fingerprint Classification, Machine Graphics and Vision, 8 (2) 241-248, 1999

[Cappelli 1999 b] R. Cappelli, A. Lumini, D. Maio, and D. Maltoni, Fingerprint Classification by Directional Image Partitioning, IEEE Transactions on Pattern Analysis and Machine Intelligence, 21 (5) 402-421, 1999

[Neuhause 2005] M. Neuhaus and H. Bunke, A Graph Matching Based Approach to Fingerprint Classification Using Directional Variance, Proc. of 5th Int. Conf. on Audio- and Video-Based Biometric Person Authentication AVBPA'05, T. Kanade, A.K. Jain, N. Ratha Eds., Springer LNCS 3546, pp. 191-200, 2005.

[Neuhause 2005 b] M. Neuhaus and H. Bunke, Graph-Based Multiple Classifier System - A Data Levels Fusion Approach, Proc. of 13-th Int. Conf. on Image Analysis and Processing ICIAP'05, F. Roli and S. Vitulano Eds., Springer LNCS 3617, pp. 479-486, 2005.

[Senior 2001] A. Senior, A Combination Fingerprint Classifier, IEEE Transactions on Pattern Analysis and Machine Intelligence, 23 (10) 1165-1174, 2001

[Cappelli 2002] R. Cappelli, D. Maio, and D. Maltoni, A Multi-Classifier Approach to Fingerprint Classification, Pattern Analysis and Applications, 5 (2) 136-144, 2002

[Marcialis 2003] G.L. Marcialis, F. Roli, and A. Serrau, Fusion of Statistical and Structural Fingerprint Classifiers, Proc. of 4th Int. Conf. on Audio- and Video-Based Person Authentication AVBPA'03, (June, 9-11, 2003, Guildford, U.K.), J. Kittler and M.S. Nixon Eds., Springer LNCS 2688, pp. 310-317, 2003

[Serrau 2005] Serrau, A., Marcialis, G., Bunke, H., Roli, F.: An experimental comparison of fingerprint classification methods using graphs. In: Proc. 5th Int. Workshop on Graph-based Representations in Pattern Recognition. (2005)

[Maio 1996] D. Maio, D. Maltoni, A Structural Approach to Fingerprint Classification, Proc. 13th ICPR, Vienna, pp. 578-585, 1996

[Windeatt 2003] T. Windeatt and F. Roli (Eds.), Multiple Classifier Systems, LNCS 2709, Springer Verlag, 2003

[Frasconi 1998] P. Frasconi, M. Gori, and A. Sperduti, A General Framework for Adaptive Processing of Data Structures, IEEE Transactions on Neural Networks, 9 (5) 768-786, 1998

[Yao 2001] Y. Yao, G.L. Marcialis, M. Pontil, P. Frasconi, and F. Roli, A New Machine Learning Approach to Fingerprint Classification, Proc. of 7th Congress of the Italian Association for Artificial Intelligence AIIA'01 (Bari, Italy, September 2001), F. Esposito Ed., Springer LNAI 2175, pp.57-63, 2001

[Sperduti 1997] A. Sperduti and A. Starita, Supervised neural networks for the classification of structures, IEEE Transactions on Neural Networks 8 (3) 714-735, 1997

[Pollack 1990] J.B. Pollack "REcursive distributed representations" Artificial Intelligence 46 (1-2) 77-106, 1990

[Plate 1995] T.A. Plate "Holografic reduced representation" IEEE Transactions on Neural Networks 6(3) 623-641, 1995

[Goller 1996] C. Goller and A. Kuchler, Learning task-dependent distributed structure-representations by backpropagation through structure, in: IEEE International Conference on Neural Networks, 347-352, 1996

[Frasconi 2001] P. Frasconi, M. Gori, and A. Sperduti, Special Section on connectionist models for learning in structured domains, IEEE Transactions on Knowledge and Data Engineering, 13 (2), 2001

[Bishop 1995] C.M. Bishop, Neural Networks for Pattern Recognition, Oxford University Press, 1995

[Marcialis 2001] G.L. Marcialis, F. Roli, and P. Frasconi, Fingerprint Classification by Combination of Flat and Structural Approaches, Proc. of 3rd International Conference on Audio- and Video- Based Biometric Person Authentication AVBPA'01 (Halmstad, Sweden, 3-5 June 2001), J. Bigun and F. Smeraldi Eds, Springer LNCS 2091, pp. 241-246, 2001

[Breiman 1996] Breiman, L.: Bagging predictors. Machine Learning 24 (1996) 123140

[Ho 1998] T. K. Ho, The Random Subspace Method for Constructing Decision Forests, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 20, 8, pp. 832-844, August 1998.

[Schenker 2004] A. Schenker, H. Bunke, M. Last, A. Kandel, "Building graph-based classifier ensembles by random node selection", Proc. of 5th International Conference on Multiple Classifier System MCS'04 (Cagliari, Italy, June 2004), F. Roli, J Kittler, T. Windeatt Eds, Springer LNCS 3077, pp. 214-222, 2004.

[Skurichina 2000] M. Skurichina, S. Raudys, and R.P.W. Duin, K- Nearest Neighbors Directed Noise Injection in Multilayer Perceptron Training, IEEE Transactions on Neural Networks, vol. 11, no. 2, 2000, 504-511

[Bunke 1983] H. Bunke and G. Allermann, Inexact Graph Matching for Structural Pattern Recognition, Pattern Recognition Letters, 1 245-253, 1983.

[Watson 1992] C.I. Watson and C.L. Wilson, NIST Special Database 4, Fingerprint Database, U.S. National Institute of Standard and Technology, 1992.

[Chow 1970] C.K. Chow, On optimum recognition error and reject tradeoff, IEEE Transactions on Information Theory, 16:41-46, 1970.

[Roli 2002] F. Roli, F. Kittler, 2002. Multiple Classifier System. Springer-Verlag, Lecture Notes in Computer Science, Vol. 2364.

[Kittler 1998] J. Kittler, M. Hatef, R.P.W. Duin, J. Matas, 1998. On Combining Classifiers. IEEE Transactions on Pattern Analysis and Machine Intelligence, 20 (3) 226-239.

[Giacinto 1997] G. Giacinto, F. Roli, 1997. Ensembles of Neural Networks for Soft Classification of Remote Sensing Images. European Symposium on Intelligent Technologies, 20-21 March, Bari, Italy, pp.166-170