METHODS AND APPLICATIONS FOR FORENSIC SCIENCES

Settore scientifico-disciplinare  ING-INF/01 Elettronica

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ACADEMIC YEAR 2010/2011
Sommaro

La scienza forense è quella branca della scienza che si occupa dell’analisi del materiale probatorio. Lo scopo di questa analisi è quello di comprendere le dinamiche del delitto, al fine di trovare il colpevole. In questo lavoro sono stati studiati tre nuovi metodi per affrontare alcuni dei problemi che devono affrontare gli esperti di scienze forensi.

Il primo è un sistema per l’identificazione automatica delle calzature, al fine di trovare la marca e il modello della scarpa che ha lasciato l’impronta sulla scena del crimine. Un algoritmo basato sulla distanza di Mahalanobis è stato impiegato per lo scopo ed è stato confrontato con altri sistemi disponibili in letteratura sia su tracce di scarpa sintetiche che su tracce di scarpa reali, ovvero sia tracce prodotte aggiungendo sinteticamente rumore che tracce provenienti dalla scena del crimine, rispettivamente.

In un secondo sistema studio è stato analizzato lo spettro di terzo ordine, cioè il bispettro. Il bispettro può essere utilizzato per restaurare segnali corrotti, ma molti degli algoritmi disponibili soffrono per la comparsa di una traslazione sconosciuta nel segnale ricostruito. L’algoritmo proposto esegue la ricostruzione utilizzando direzioni parallele del dominio del bispettro e offre una soluzione semplice per risolvere e dimostrare la soppressione del problema nel caso di segnali 1D.

Nell’ultimo sistema studiato, viene svolta l’analisi di impronte digitali utilizzando tecniche non standard. Un microspettrometro a trasformata di Fourier nell’infrarosso (FT-IRMS) viene utilizzato per analizzare il contenuto delle impronte digitali. L’FT-IRMS produce un’immagine iperspettrale, e il sistema proposto elabora ognuno degli spettri prima stimando il numero di gruppi funzionali che lo compongono e poi individuando i loro parametri. A completamento del quadro, sono state impiegate diverse metodiche basate sui raggi x per lo studio degli eventuali contaminanti presenti nell’impronta.
Abstract

Forensic science is the branch of science dealing with the analysis of evidence material. Its aim is to understand the dynamics of the crime, in order to find the culprit. In this work three new methods have been studied as an aid for the forensic experts.

The first one is a system for the automatic retrieval of footwear to find the make and model of the shoe that left its mark on the crime scene. A Mahalanobis distance based algorithm is employed for the purpose and is compared with other systems available in literature on both synthetic and real shoe marks, i.e. on both computer generated shoe marks and on marks coming from crime scene.

In a second study the third order spectrum, i.e. the *bispectrum*, is analyzed. The bispectrum can be used to restore corrupted signals but many available algorithms suffer for the emergence of an unknown translation in the reconstructed signal. Here the procedure is performed using two parallel paths in the domain of the bispectrum and a simple solution to the unwanted translation is found and demonstrated in the case of a 1D signal.

Finally, fingerprint analysis is performed using non standard techniques. A Fourier transform infrared microspectroscope (FT-IRMS) is used to analyze the content of fingerprints. The FT-IRMS produces a hyperspectral like image and the proposed system processes each spectrum to estimate the number of functional groups and to give their parameters. Finally contained contaminants have been studied with several x-ray based techniques to give a comprehensive picture of the fingerprint evidence.
Methods and applications for forensic sciences

Federico Cervelli

February 14, 2012
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Introduction

Forensic science is the branch of science dealing with the analysis of evidence material. Its aim is to help the criminal justice system to find and punish those who behaved against the law and against society, individuals and their rights.

Although the name immediately suggests classical and recent investigative techniques, like fingerprint comparison and DNA analysis, the term is quite undefined and comprises all branches of human knowledge and technology that can help the operators of the justice system in their tasks. Accounting, physics, civil and marine engineering, fabric production, cosmetics analysis, information technology, palynology, entomology, etc. all fall under the interest of forensic science.

In this regard image and (more in general) signal processing have a lot to offer to forensic science as they can be part of the evidence, e.g. the footage of a robbery acquired by the CCTV system of the bank, or they can give a valuable help during evidence analysis and interpretation, e.g. looking for the unknown culprit fingerprint in the national fingerprint database.

Thus, in this work three different fields are explored and researched in order to give forensic experts some state of art and effective methods in their mission.

The thesis is organized as follows:

Chapter 1 A look to the idea at the very base of forensic science is given: the comparison between a known and unknown item is the guide of all the investigations, and image and signal processing can be really helpful to this approach.

Chapter 2 A system for the automatic retrieval of footwear is setup and tested in order to find the make and model of the shoe sole that left its mark on the crime scene. A novel algorithm is proposed and tested on synthetic and real
shoe marks coming from crime scene.

**Chapter 3** Higher order spectra analysis can be used to restore a corrupted signal. However it suffers the emergence of an unwanted translation in the restored signal that can be detrimental in some cases. This problem is addressed and solved, and the proposed simple solution is demonstrated with a 1D simulation of a turbulent signal.

**Chapter 4** Fingerprints are analyzed with unconventional techniques typical of biological and material science experiments. Using the facilities available at a synchrotron source, fingerprints are mapped in order to obtain their morphology and their endogenous and exogenous contents.
Chapter 1

Forensic image and signal processing

The field of forensics science has attracted more and more momentum recently as can be inferred from the never ending TV series inspired by the world of the “white coats investigators”. These productions have caught the attention of the citizens, and there is now a strong awareness and expectation of the possibility offered by science at the service of justice.

In this chapter the general problem of the expert of forensic science will be introduced and it will be clear how information technology engineering, like all areas of advanced research, can provide an important complement to forensic sciences in an attempt to ensure the prosecution of the perpetrators of crimes.

1.1 The problem of forensic sciences

The Forensic Science is doubly connected to the crime scene, which is the starting point of the investigation, be it classical or scientific.

As a matter of fact the crime scene experts start their inspection from the crime scene scene looking for items related to the offense in order to use them to identify the culprit, or, at least, functional to direct investigations on the right path. The search for evidence* usually leads to the discovery of objects of unknown origin

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*The evidence can be either evident, as in the case of a bloody knife, or latent, as in the case
that must be analyzed in order to be informative.

The analysis required is a *comparison*, which serves several purposes:

- establish the class, i.e. a product group (e.g. an adhesive tape, a fabric, a fingerprint, etc.);

- determine the general characteristics of the class (e.g. double-sided tape, jeans, bidelta fingerprint, etc.);

- identify the characteristics of the object that caused the evidence (e.g. Scotch tape, Levi’s jeans, the print of the middle finger of the right hand of John Doe, etc.);

so that the source or cause of formation of the evidence can be identified as precisely as possible.

Some examples are given below:

- the tissue found at the scene of the crime can be traced back to the jeans trousers of the suspect;

- the marks on the window frame, Fig 1.1 and 1.2, correspond to those that might have been caused by the screwdriver seized to a person under investigation;

- a fingerprint found in the bank shares the same pattern and minutiae configuration of the middle finger of the right hand of a subject inserted in the national fingerprint database.

This is therefore a comparison between an unknown object found at the crime scene and one or more known objects, possibly organized in a DB and directly or indirectly connected to someone.

### 1.2 Comparison steps

The forensic expert must then analyze the items collected at or connected to the crime scene and establish a link between these evidential items and the unknown of gunshot residues.
Figure 1.1: Example of comparison: on the left the marks left on the window frame by an unknown screwdriver use to open the window itself; on the left the marks produced using a known screwdriver seized to a suspect (red arrows indicate corresponding marks).

Figure 1.2: The identification of the screwdriver is possible because its usage had caused the formation of unique accidents, which are responsible of the marks on the window frame.
culprit.

The *ACE-V* acronym is often used [Ash99, Van04, SWG, Int] to denote the procedure to be followed by the expert in order to effectively compare images and express a conclusion:

**Analysis**: evidence and the known terms of comparison are analyzed to extract possibly unique and identifying features that describe or distinguish them;

**Comparison**: the special features are used to compare the evidence with the known terms of comparison;

**Evaluation**: the expert evaluates the degree of correspondence between the evidence and all available terms for comparison, in order to extract the evidence-known term couple with the higher degree of correspondence;

**Verification**: all process is subjected to the critical review of another expert who confirms or disproves the conclusion reached by the previous expert.

### 1.3 Conclusions scale

At the end of the aforementioned comparison the expert expresses his or her judgment through a *conclusions scale*, organized as follows*

- the terms compared are *compatible*;

- the terms of comparison are *not compatible*;

- the comparison of the terms gives an *intermediate* result between compatibility and incompatibility.

The conclusions scale is structured on different levels† and can be either qualitative (expressed using human language) or quantitative (expressed in terms of numbers).

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*Here we consider the case where the source of evidence has enough quality to effect a comparison.

†A special case is fingerprint conclusions scale, divided only on the levels of identity (compatible) and exclusion (not compatible).
1.4 Image and signal processing: helping the forensic expert

During investigations it is required to perform all activities that may provide useful information to reconstruct the circumstances and the actors of the offense. Thus also the technical and scientific investigations are part of this activities as they offer the best in all areas of science and research to help justice.

However it should be noted that whatever the technology used, it is always and only an aid to the expert: the result presented by the algorithm does not constitute the final stage or the final judgment of the investigation and the expert needs to evaluates the suggestion of the algorithm with the right to judge it final or not, and can also evaluate it in a different way.

Table 1.1: Example of conclusions scale for shoe marks comparison (taken from [Com06]).

<table>
<thead>
<tr>
<th>Level</th>
<th>Likelihood Ratio (partial Bayes’ rule)</th>
<th>Probability (full Bayes’ rule, classical approach)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Identification</td>
<td>Identification</td>
</tr>
<tr>
<td>2</td>
<td>Very strong support for proposition A</td>
<td>Very probably proposition A</td>
</tr>
<tr>
<td></td>
<td>Strong support for proposition A</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Moderately strong support for proposition A</td>
<td>Probably proposition A</td>
</tr>
<tr>
<td></td>
<td>Moderate support for proposition A</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Limited support for proposition A</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Inconclusive</td>
<td>Inconclusive</td>
</tr>
<tr>
<td></td>
<td>Limited support for proposition A</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Moderate support for proposition A</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Moderately strong support for proposition A</td>
<td>Likely not proposition A</td>
</tr>
<tr>
<td></td>
<td>Strong support for proposition A</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Very strong support for proposition A</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Elimination</td>
<td>Elimination</td>
</tr>
</tbody>
</table>

The conclusions scale for the comparisons of shoe impressions is shown in Fig. 1.1 as an example.

1.4 Image and signal processing: helping the forensic expert

During investigations it is required to perform all activities that may provide useful information to reconstruct the circumstances and the actors of the offense. Thus also the technical and scientific investigations are part of this activities as they offer the best in all areas of science and research to help justice.

However it should be noted that whatever the technology used, it is always and only an aid to the expert: the result presented by the algorithm does not constitute the final stage or the final judgment of the investigation and the expert needs to evaluates the suggestion of the algorithm with the right to judge it final or not, and can also evaluate it in a different way.
An example [MMJP09] is provided by the automatic fingerprints identification system (so-called AFIS) currently in use by police forces. The procedure is as follows:

- the unknown fingerprint is found at the crime scene;
- the evidence is inserted into the AFIS;
- the system compares the unknown print with each fingerprint present in the database;
- the system estimate the degree of compatibility between the evidence and every known items;
- the AFIS creates a list showing to the expert the known terms in order of decreasing compatibility;
- only fingerprints with higher degree of compatibility are shown (e.g. the 50 most compatible);
- the expert reviews the proposed list and judges the results, possibly identifying the fingerprint.

This same procedure applies to all branches of forensic science and information engineering with image and signal processing gives an invaluable help to forensic experts.
Chapter 2

Automatic footwear retrieval of crime scene shoe marks

The activities of the crime scene investigators are key to solve the crime and find the culprit, and mainly rely on the search for useful evidence [JN05]. In particular, shoe prints left on the crime scene, the so called shoe marks, allow the prosecutor and the police officers to lighten the crime dynamics [Gir97]: with no suspect or few elements available, the knowledge of the make and of the model of the shoe that left the shoe print on the scene is a valuable information towards the solution of the case.

Citing a classical in the field [Bod99]:

Crimes involve people and places. Persons committing a crime leave footwear impressions an route to, at, and exiting from the crime scene […] In many instances, footwear impressions can be positively identified as having been made by a specific shoe to the exclusion of all other shoes […] The identification is as strong as that of fingerprints, toolmarks, or typewritten impressions.

Obviously this is not an easy task: sole design doesn’t obey standards, except for the trend and the special needs for shoes made with a purpose (boat shoes, tennis shoes, trekking shoes, work shoes, etc.). Thus the pattern on the shoe soles can vary wildly, Fig. 2.1, with few if not any chances to find a criterion.

Moreover, shoe soles:
Automatic footwear retrieval system

- can leave prints on different material (e.g. paper, wall, metal, plastic, fabric) characterized by different properties and textures [Bod99];
- can leave the shoe marks both by removing or depositing different material (e.g. mud, snow, earth, blood, dust);
- can produce 2D or 3D marks, like those made in snow, mud and earth;
- can be developed and acquired by several different techniques, thus affecting the overall appearance of the shoe mark image.

This field is an increasing research topic in content based image retrieval systems and some systems for semi-automatic and automatic footwear retrieval have been already proposed. However they all have been tested on synthetic shoe marks, i.e. sole prints with added synthetic noise.

This chapter gives a description of the problem of automatic search of the design of shoe soles, used in scientific investigations to identify the make and model of shoe that may have left the track at the crime scene. In Sec. 2.1 a review of the state of the art research on automatic footwear retrieval systems is given, in Sec. 2.4 the setup of the test is shown, while the different algorithms employed are described in Sec. 2.5. Finally in Sec. 2.6 the results obtained testing different systems on both synthetic and real shoe marks are given.

2.1 Footwear retrieval systems: state of the art

The common approach for the forensic expert, looking for the make and the model of the shoe which produced the shoe mark on the crime scene, is to analyze the shoe mark and to search the corresponding shoe on electronic and paper catalogs.

Another emerging approach is to query a reference database of shoe soles with the crime scene shoe mark, and analyze the higher ranking results of the query. Both semi-automatic and automatic systems have been proposed to answer this request.

In [Gir96, Saw95, Ash96] semi-automatic systems are realized where human expert classify shoe soles (and shoe marks) with a series of geometric patterns from a given vocabulary.
Here we give an overview of the automatic footwear retrieval systems that have been proposed in literature and among which we will choose the ones to be tested on both synthetic and real shoe marks.

In [GK96] soles and shoeprints are collected in collaboration with police forces. Shoeprints are photographed while soles are first imprinted in foam boxes (used to take anatomical impressions of the feet) and then photographed. Finally the images are scaled and compressed. The shapes of the shoe prints are labeled and then classified. Labeling is performed through binarization, while connection properties of the image binary pixels are used to segment it into shapes, Fig. 2.2. The shapes are then classified using the Fourier transform (both amplitude and phase are used). A subsequent analysis allows to take the most relevant Fourier features to describe each shape. Finally a single-hidden-layer feedforward neural network trained with back propagation is used as the recognition network. Despite the detailed description of the system building block, no clue is given about its performance, and no follow ups are available on the system.

Fractals and mean square noise error are employed in [BANC00] to represent and compare shoeprints, respectively. Fractal decomposition produces a list of spatial transformations that regenerate the original image when applied recursively to the image itself; thus the fractal transform found for the image to be
Figure 2.2: The shoe sole pattern is labeled and the constituent shapes are extracted for further analysis (image taken from [GK96]).
queried will produce small changes when applied to a similar image in the reference DB, while will cause large differences when applied to shoe print images with a different pattern, Fig. 2.3. The mean square noise error is then used as the similarity measure. The reference database (DB) is composed of 145 gray level shoe print images, whose dimension is $256 \times 256$ pxl. Test is made with the same images composing the DB but with added Gaussian noise, rotation and translation. Rotation range from $1^\circ$ to $9^\circ$, while translation ranges from 1 to 13 pxl. Reported results give 60% correct match at $9^\circ$ rotation and a severe drop to 10% after a 10 pxl translation.

![Fractal Decomposition Diagram](image)

Figure 2.3: The fractal decomposition computed on the shoemark regenerate the original shoemark only when applied recursively to the originating image (image taken from [BANC00]).

Fourier transform is implemented in [DFR05]. The power spectral density (PSD) is calculated and used to characterize the images, in order to have translational invariance. The used similarity measure is based on the 2D correlation
Figure 2.4: Power spectral density is computed on the pre-processed sole images and then rotated to obtain rotation invariance (image taken from [DFR05]).

The power spectral density (PSD) coefficient between the PSD of the query image and that of the DB elements. Rotational invariance is forced through rotation of the query image in the range $\pm 30^\circ$, Fig. 2.4. The reference DB is built taking shoe prints of volunteers. A total number of 476 full shoeprints is acquired ($4096 \times 4096$ pxl size, downsampled to $64 \times 64$, $128 \times 128$, $256 \times 256$ and $512 \times 512$ pxl). All 476 shoe prints have repetitions, i.e. each sole pattern has been acquired at least twice, thus he DB is really made of 140 different soles; also 63 partial prints have been acquired and each full print has been divided in halves and quarters for a total of 8 partial shoe prints produced for each of the 476 full prints. All these shoe prints (full and partial) are used in turn to query the remaining 475 elements of the DB. Average Match Score and Cumulative Matching Characteristic are used to optimize the system parameters and to assess it, respectively. Results show that shoe prints are correctly matched in the first 5% of the sorted DB patterns with an 85% score. Here noisy images are not considered.

Phase only correlation of the Fourier transforms (FFT) of the shoeprints is employed in [GBC07], reason being that the phase information is much more important than the FFT amplitude in preserving the features of image patterns, Fig. 2.5. The reference DB is made of 100 elements (gray level, $512 \times 512$ pxl size) which are also used to generate synthetic shoe marks. Four sets of synthetic shoe marks are created: set 1 contains 400 clean partial shoeprint obtained by dividing each original complete shoeprint into four quarters, set 2 contains 2000 noisy partial shoeprint images obtained by adding white Gaussian noise to each partial shoeprint of set 1, set 3 contains 2000 blurred partial shoeprint images obtained...
applying motion blur to the images of set 1. Finally set 4 contains 2000 partial shoeprints images obtained by pasting each image from set 1 into five texture images from the Brodatz album [Bro66]. The simulated shoe marks are queried to the reference DB of 100 items, demonstrating a 100% first rank recognition rate, i.e. the queried image is always found at the first place by the algorithm.

More recently region-based invariants were used in [AA08]. Hu’s seven moments \( \varphi_1, \ldots, \varphi_7 \) are invariant under translation, rotation and scaling and are analyzed to characterize a DB containing 500 shoeprint images. A feature vector \( \vec{f} \) based on the Hu’s moments can be associated to an image: \( f_i = 0 \) if \( \varphi_i = 0 \), and \( f_i = |\log(\varphi_i)| \), if \( \varphi_i \neq 0 \), where \( i = 1, \ldots, 7 \), and the analysis shows that the first and the second moments are the most discriminating. The DB images are synthetically corrupted by zero mean Gaussian noise with variance from 1 to 20%, and then queried against the full DB; tests are made also with different resolution (from 6 to 200 dpi) and rotation (from \(-90^\circ\) to \(+90^\circ\)). Then Euclidean distance, city block distance, Canberra distance and correlation distance are tested as similarity measures, and correlation distance is chosen. Results show that accuracy drops to 61% for a 5% variance, and to 5.4% for a 20% variance. DPI and rotation tests are performed with null or 1% variance, and demonstrate a 98% recognition rate for 6 dpi and a 100% value for all rotations.

A Maximally Stable Extremal Region (MSER) detector is used in [PA09] to identify the features of the shoeprint and the Scale Invariant Feature Transform (SIFT) algorithm is employed to describe them. The MSER is a watershed-based
segmentation algorithm, characterized by good repeatability under affine transformations and image degradations (e.g. blur, lightning, etc.). The SIFT descriptor can be employed when partial or hidden data are to be compared. The method is based on the image gradient location and orientation histogram built using eight quantized orientations and a $4 \times 4$ grid, with a resulting descriptor of dimension 128. Each shoe pattern is encoded in terms of the individual features relative to a codebook, built by pooling together all the features descriptor from the pattern database and then using $k$-means clustering to quantize this data into a fixed number of bins. Each pattern is then encoded using term frequency-inverse document frequency (tf-idf) weighting. This increases the importance given to features proportionally by the number of times they appear in a pattern but is offset by their frequency in the whole database. After this first step a shorter list remains, and a finer search proceeds by comparing the shoeprints through a modified constrained spectral correspondence method, Fig. 2.6. The reference DB is made of 374 shoeprints, left and right print, while the test set is made of an image of either a complete left or right print. The DB and test items have a 50 dpi resolution (and 600×600 or 300×600 pxl size). Results demonstrate that if the system provides a user with a top-8 (top-16) display of similar patterns, the correct one will be within this short-list about 91% (93%) of the time. They also report a 94% classification rate from viewing only 5% of the database.

More recently a shape based classification algorithm has been proposed [TSK10].
2.2 Limits of the current methods

In the work they use the Hough transform and modified Hough transform to find lines, circles and ellipses in the sole print image, Fig. 2.7. Then an attributed relational graph (ARG) for each sole print is built to characterize the sole itself with the relation among the above extracted lines, circles and ellipses, Fig. 2.8. The footwear print distance is defined as the distance between different soles ARGs configurations. The system is built in a way to be invariant to translation, rotation, and scale, however no performance results or reference DB number are given.

At the end of this chapter we will make a comparison of the most successful methods described above, i.e. the ones in [DFR05] and [GBC07], and the method proposed in this thesis, on both synthetic and real shoe marks coming from crime scenes. This last comparison has never been done before at the best of our knowledge, and this is a serious research lack, given that simulated shoe marks may not represent real shoe marks found on the crime scene [KLV98, JDM00, PRMN04].

2.2 Limits of the current methods

The analysis of the state of the art in automatic footwear retrieval systems research shown in the previous section is not complete and other works could be mentioned [?]. However it is clear that this research field is still young and it is mainly devoted to the application of known algorithms to this particular problem.
Figure 2.8: Once extracted the shapes they are identified as points on the sole, A), and then linked to build an attributed relational graph which stores the configurations of nearby shapes, B); the red box mentioned in B) is visible in Fig. 2.7.H) (image taken from [TSK10]).
2.2 Limits of the current methods

(only exception being perhaps [TSK10]). In fact the works recalled in Sec. 2.1 use commonly used methods, like classical Fourier transform descriptors, Hu’s moments or SIFT-like methods.

A deeper analysis allows to note another characteristic common to all cited works, i.e. the choice to test the proposed algorithms on “fake” shoe marks either produced adding synthetic noise or using good quality shoe prints, rather than on real shoe marks found at the crime scene.

Finally, due to the lack of a publicly available database for testing purpose (as is the case for other biometrics and forensic research field), each group has built and uses its own reference database and fake shoe marks, with few if not any chance to compare results with other studies.

Moreover also the given results are not given in a common format. The most used reporting methods are:

- tabular form, given as tables with the percentage of times the system is able to find the correct shoe print in the first \( N \) items of the ranked list, Fig. 2.9.A);

- cumulative match curve (CMC) [PMRR00], which answers the question “What is the probability of a match if I look at the first \( N \) percent of the ranked list?”, Fig. 2.9.B).

Only recently groups seem to have aligned using CMCs, which offer a clear and comprehensive way to represent results.

In Tab. 2.1 a summary is given with the results of the different systems, showing, from left to right:

- literature reference;

- employed algorithm;

- invariance of the system: “t” for translation, “r” for rotation, “s” for scale invariance;

- number of sole print images in the reference database;

- number of shoe marks;
Figure 2.9: Example of results reported in tabular form, A), and using the cumulative match curve, B); in red the values of 87% and 70% matching probability in case of a ranked list length equal to 5% of the reference DB length, respectively for full and partial print images (image taken from [DFR05]).

- system results.

The numbers shown on the right most column in Tab. 2.1 are adapted to offer a common point of view, given the difference in reporting the results.

2.3 System architecture

The system under study is an image retrieval system which should be able to retrieve, from a known shoes archive, the footwear able to produce the shoe mark found at the crime scene.

This is not as strong as finding the finger which left the finger mark on the crime scene as two different subjects could buy a similar shoe model and the culprit could also wear a pair of shoes taken to someone else. However the investigative information can be very valuable when no other information is available or if the culprit shoe, after identification, can be related to other evidence (e.g. blood of the victim, fabric of the culprit clothes).

The system architecture is sketched in Fig. 2.10. A reference DB is the repository of known shoe make and models. Each item in the reference archive is an
<table>
<thead>
<tr>
<th>Work</th>
<th>Used Algorithm</th>
<th>Invariance Properties</th>
<th>Reference Shoes</th>
<th>Shoe Marks Production Methods</th>
<th>Results (3% DB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>[GK96]</td>
<td>Labeling, Fourier analysis, neural network</td>
<td>t,r</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>[BANC00]</td>
<td>Fractal decomposition, mean square error</td>
<td>None</td>
<td>32</td>
<td>rotation or translation</td>
<td>8°: 47%; 5 pxl: 47%</td>
</tr>
<tr>
<td>[DFR05]</td>
<td>Power spectral density, correlation</td>
<td>t,r</td>
<td>476</td>
<td>From DB</td>
<td>81% full; 60% partial</td>
</tr>
<tr>
<td>[GBC07]</td>
<td>Phase only correlation, maximum peak height</td>
<td>t</td>
<td>100</td>
<td>known shoes, noise, texture</td>
<td>100%</td>
</tr>
<tr>
<td>[SCBG07]</td>
<td>Modified Harris-Laplace, enhanced SIFT, thresholded nearest neighbour</td>
<td>t,r,s</td>
<td>500</td>
<td>rotation, translation, scale, noise</td>
<td>90%</td>
</tr>
<tr>
<td>[AA08]</td>
<td>Hu’s moments, different metrics</td>
<td>t,r</td>
<td>500</td>
<td>rotation or noise</td>
<td>20% noise: 5.4%</td>
</tr>
<tr>
<td>[PA09]</td>
<td>Maximally stable extremal region, term frequency-inverse document frequency, singular value decomposition</td>
<td>t,r,s</td>
<td>374</td>
<td>From DB</td>
<td>93.8% (5% rank)</td>
</tr>
<tr>
<td>[TSK10]</td>
<td>Basic features, attributed relational graph, clustering, footwear print distance</td>
<td>t,r,s</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

Table 2.1: Summary of all major research in the field of automatic footwear retrieval systems; from left to right: reference work, used algorithm, used algorithm invariance properties ("t" for translation, "r" for rotation, and "s" for scale), number of known shoe prints in the reference DB, number of shoe marks, and results. The “- - -” stands for missing information.
image depicting the print that can be left by the sole of that particular shoe. An image processing block takes care of the steps needed to describe the images. The shoe mark which is the object of investigation is inserted into the system to look for the shoes that could have left it on the crime scene. Again, an image processing block takes care of the further processing needed to describe the shoe mark.

Then a the compare block is used to define a way to measure the similarity (or the distance) between two shoe prints.

With the so defined metrics, a ranked list is prepared. This list is made with the results of the comparison and the first item in the ranked list corresponds to the reference DB sole image which is less distant from the shoe mark image; the second item in the list is the second less distant, and so on.

Finally the ranked list is proposed to the forensic expert who reviews a defined number of highest ranked items in the list* and tells if there is or is not a match.

In the following sections the setup of the reference DB and test shoe marks, the descriptors and the metrics used will be described.

2.4 Setup of the test

No public database is currently available for testing purpose, and no reference archive, no fake shoe marks and no real shoe marks are available for research.

Thus, a reference DB (RDB) was built for this research. The archive is made of known shoe soles with a known shoe print pattern; for this purpose we used the images available at the ENFSI [Eur] WGM website [oMw] and then adapted them as explained later in Sec. 2.4.2.

Then, two different sets of shoe marks were realized to test our algorithm effectiveness querying the RDB:

- a synthetic shoe marks set (SyntS), realized as detailed in Sec. 2.4.1;

- a real shoe marks set (RealS), realized starting from the images available at the ENFSI WGM website [oMw] and then adapted as explained in Sec. 2.4.2.

*This number is not fixed, and is defined after a cost-benefit analysis by the customer: the analysis looks for the optimal threshold between a) the time spent for a single N-items list review, and b) the need to find the culprit.
Figure 2.10: System architecture: each sole image in the reference DB (top-left) is described with the chosen image processing algorithm; the unknown shoe mark (bottom-left) is described with the same image processing technique; a suitable distance is used to compare the shoe mark description with each reference DB image description; finally a ranked list is proposed to the forensic expert who gives his or her judgment and tells if there is or not a match (right).
2.4.1 Synthetic shoe marks set

The purpose of the test is to make a comparison with other previously published works. However, a standard database does not exist yet on which to carry on performance comparisons. Moreover, all other existing works only consider synthetic shoe marks.

Starting from the RDB, described in Sec. 2.4.2, we have created two subsets of synthetic shoe marks, following the procedure employed in [GBC07] for the same purpose:

- Subset 1: 340 shoe marks obtained by adding a white gaussian noise to each shoe print in the RDB; the MATLAB function `imnoise` is used, with zero mean and variance $\sigma^2 = 1, 5, 10$ and 15%;

- Subset 2: 425 shoe marks obtained by blurring each sole print in the RDB; the MATLAB functions `imfilter` and `fspecial` were used, with zero angle and length $d = 2, 5, 10, 15$ and 20 pxl (corresponding to 0.15, 0.37, 0.75, 1.13 and 1.5 cm).

Some samples of the above subsets are shown in Fig. 2.11 and Fig. 2.12, for Gaussian noise and motion blur respectively.

2.4.2 Reference DB and real shoe marks set

The images were first converted to gray scale and subjected to a rough resize and rotation, in order to have an approximate correspondence in size and orientation between the soles and the marks. Then one or more zones of interest of 100×100 pixel size were cropped and used for the test, Fig. 2.13. Cropping was performed also for the crime scenes shoe marks in order to increase their number for testing purposes.

Following this procedure and starting from the images available on the ENFSI WGM website, we built both a reference DB made of 85 known shoe sole crops (corresponding to 25 known shoes) and a real shoe marks set made of 35 items (corresponding to 16 known shoes).
2.5 Proposed methods

Two different algorithms were tested during this research. The first one is based on the Mahalanobis distance, used to map pixel luminance values inside the sole images, Sec. 2.5.1. The second one is based on the correlation between the phases of the Fourier transforms of the shoe mark and of the reference DB shoe print images, Sec. 2.5.2.

2.5.1 Mahalanobis distance map

The descriptor employed is used to represent the textured regions in shoe soles. This representation is based on the geometrical structures of objects, as proposed in [UT02] where it was used to detect human figures. As we can not assume particular pixel value patterns for objects like shoe marks found at crime scenes, we focus on geometrical structures observed as distances between pixel value pat-
terns. Here, the pixel values are just labels making some regions stand out against other regions, because the variety of colors and textures of possible background where shoe marks can be found is enormous. Conversely, the relative positions and shapes of different parts in the sole print texture region are common for a given shoe model. We select the proposed descriptor in order to focus more on geometrical entities rather than on pixel values themselves. So we extract the geometrical structures of our target object: this method is similar to edge based object recognition methods, but methods based only on edge detection are generally too sensitive to local information and are not robust against noise. The proposed descriptor is applied on gray scale shoe print and shoe mark images either directly or after performing edge detection, in order to both overcome the aforementioned disadvantages of edge detection methods and improve recognition rate. The descriptor started as an human operator aided system [CDC09b, CDC09c] and was then developed further in a full automatic system [DCC09a, DCC09b].

Figure 2.12: Synthetic shoe marks after blurring: A) 2 pxl (0.15 cm), B) 5 pxl (0.37 cm), C) 10 pxl (0.75 cm), D) 20 pxl (1.5 cm). Refer to Fig. 2.11.A) for the original image.
Figure 2.13: Examples of some shoe marks (top), and the expected matching shoes in the reference DB (bottom).

Descriptor

The gray scale image area that we are interested in is divided into several sub-regions or blocks, and the distances between all possible block pairs are calculated. More in detail, for an image $x(s, t)$ the area is divided into small blocks of size $p \times q$. The result is $M$ blocks in the horizontal direction and $N$ blocks in the vertical direction. Each block is identified with a number ranging from 1 to $M \times N$ in order to distinguish them as block $X_1, X_2, \ldots, X_{M \times N}$, and the average value, $\bar{x}_l$, and variance $\sigma^2_l$ are computed for each block $X_l$. Then the Mahalanobis distance [GW08] between all possible block pairs, $d(i, j)$ with $i, j = 1, \ldots, M \times N$, is calculated:

$$d(i, j) = (\bar{x}_i - \bar{x}_j)(\sigma^2_i + \sigma^2_j)^{-1}(\bar{x}_i - \bar{x}_j).$$

(2.1)
and the Mahalanobis map \( \mathcal{M} \) is determined:

\[
\mathcal{M} = \begin{pmatrix}
0 & d(1, 2) & \cdots & d(1, MN) \\
d(2, 1) & 0 & \cdots & d(2, MN) \\
\vdots & \vdots & \ddots & \vdots \\
d(MN, 1) & d(MN, 2) & \cdots & 0
\end{pmatrix}.
\] (2.2)

We use a 4 \( \times \) 4 pixel block size for the calculation, for a total amount of 25 \( \times \) 25 blocks (the employed images are 100 \( \times \) 100 pixel).

Finally the power spectral density of \( \mathcal{M} \) is calculated and used as the descriptor of the sole print and shoe mark images.

Three shoe prints and their Mahalanobis maps are shown as an example in Fig. 2.15, while the PSDs of their Mahalanobis maps are shown in Fig. 2.14.

**Mahalanobis distance map processing steps**

In order to take care of the different noise sources affecting the shoe marks, the PSD is computed on the Mahalanobis map either calculated directly on the gray scale values of the image, or after the application of a suitable operator to enhance texture. In fact, shoe marks coming from crime scenes are affected by several different sources of noise caused by different conditions of production and by the different nature both of the shoe mark material (e.g. blood, dust, paint, etc.) and of the surface on which it is produced (e.g. sand, snow, mud, textured backgrounds, etc.). Thus, the Mahalanobis map can be computed directly on the gray scale image or after histogram equalization to enhance the shoe mark texture. In our case histogram equalization is performed if the standard deviation of the gray scale image lies under an experimentally found threshold \( \sigma_S \).

If enhancement is required, it can be useful to combine its application with an edge detection algorithm before evaluating the Mahalanobis map. Luminance based Mahalanobis map is more suited for shoe mark images affected by a higher level of noise which does not allow the correct extraction of the edges. On the other hand, edge detection performs better when edges of the shoe mark can be extracted efficiently. The choice between these two methods can be based on the standard deviation values of the Mahalanobis map evaluated on the gray scale image which should then be comprised between the experimentally found values \( \sigma_L \).
Figure 2.14: Example images: the left column shows two regions coming from the same shoe A) and C) and one coming from a different one E), while the right column shows the corresponding Mahalanobis maps (as described in the text); while map B) resembles map D), note the difference between map B) and F), and D) and F).
Figure 2.15: Example images: the left column shows two regions coming from the same shoe A) and C) and one coming from a different one E), while the right column shows the PSD of the corresponding Mahalanobis maps.
2.5 Proposed methods

Begin

\( \sigma < \sigma_S \) ?

YES

Equalize histogram

Mahalanobis map

\( \sigma \in (\sigma_L, \sigma_H) \) ?

YES

Mahalanobis image edge detection

NO

PSD evaluation

NO

End

Figure 2.16: Block diagram to evaluate the PSD based descriptor.

and \( \sigma_H \). This second condition can be explained as follows: the amount of image edges obtained after enhancement has to be enough to permit pattern recognition but not so large to be likely to depend on noise.

The overall block diagram to evaluate the Mahalanobis map based descriptor is shown in Fig. 2.16.

**Combining the Mahalanobis distance map with other algorithms**

The above described descriptor proved to be robust to noise, as experimental results will show in Sec. 2.6. Thus its usage was combined together with another algorithm, i.e. the modified phase-only correlation method [GBC07], which performs better than the proposed Mahalanobis method with less noisy shoe marks.

The system [DCC09a] applies the Mahalanobis map based method to select a subset of the reference DB. The subset is composed by the \( P \) highest ranked sole extracted from the reference DB. The phase based descriptor is then evaluated on this subset and the \( Q \) highest ranked results are finally shown to a human expert who selects the database shoe that matches the shoe mark image (if a match
exists).

In another approach [DCC09b] in order to extract the \( N \) best matches to the query image from the reference DB, the following decision criteria is added to obtain the optimal trade-off between the Mahalanobis map based and MPOC methods:

- the MPOC method is applied on the shoe mark and on the reference DB images; then, if the maximum correlation value is above an experimental threshold \( r_{MP OC} \), the \( N \) highest ranked results are extracted; otherwise, we consider the MPOC method not reliable enough (probably because of noise) and we select a smaller number \( N_{MP OC} \) of highest rank results and proceed with the following step;

- the Mahalanobis map based method is applied on the shoe mark and on the reference DB images, then the \( N_{Mahal} \) highest rank results are extracted, in order to obtain \( N = N_{MP OC} + N_{Mahal} \) results. Thus, we apply the Mahalanobis map method only if required, i.e. if noise level can compromise the recognition performance of the MPOC method.

The \( N \) extracted results can be finally shown to a human expert who selects the extracted reference DB image that matches the shoe mark image (if a match exists).

**Similarity measure**

The PSD descriptor is calculated for each sole print image in the reference DB, and for the input shoe mark image. Descriptors for the DB images are evaluated either without performing enhancement operations (obviously not necessary on well defined images), or by introducing edge detection before computing the Mahalanobis map if the input shoe mark image requires it. Then a PSD based similarity measure between the descriptor of the mark and the descriptor of each items in the DB is computed and used to rank the results.

The proposed measure of similarity between the shoe mark image and the image in the DB is their correlation coefficient. For two 2D signals \( f_i(x, y) \) and
2.5 Proposed methods

Let \( f_j(x, y) \) of size \( s \times t \), the correlation coefficient, \( r_{i,j} \), is calculated using [Rus95]:

\[
\hat{f}_i(x, y) = \frac{[f_i(x, y) - \text{mean}(f_i)]}{\text{std}(f_i)}
\]  

(2.3)

\[
r_{i,j} = \frac{1}{st} \sum_{x=1}^{s} \sum_{y=1}^{t} \hat{f}_i(x, y) \hat{f}_j(x, y)
\]  

(2.4)

where \( \text{mean}(f_i) \) is the average value of signal \( f_i(x, y) \), and \( \text{std}(f_i) \) is its standard deviation. The highest \( P \) rank results so selected have to be processed as explained in the next subsection.

2.5.2 Fourier phase correlation

Although the Mahalanobis based method is able to address noisy shoe marks, the system itself is not suited to make comparison of images that are translated or rotated as it is not translation and rotation invariant. Thus another system was investigated which uses the translation and rotation properties of the Fourier transform.

Descriptor

Let \( f_1(x, y) \) and \( f_2(x, y) \) be two images differing only by a displacement \( (x_0, y_0) \), so that [CDD94]:

\[
f_2(x, y) = f_1(x - x_0, y - y_0).
\]  

(2.5)

Their Fourier transforms \( F_1(\xi, \eta) \) and \( F_2(\xi, \eta) \) are related by:

\[
F_2(\xi, \eta) = e^{-j2\pi(x_0+y_0)} F_1(\xi, \eta)
\]  

(2.6)

and the cross-power spectrum \( Q_{1,2} \) of \( f_1(x, y) \) and \( f_2(x, y) \) is given by:

\[
Q_{1,2}(\xi, \eta) = \frac{F_1(\xi, \eta)F_2^*(\xi, \eta)}{|F_1(\xi, \eta)F_2^*(\xi, \eta)|} = e^{j2\pi(x_0+y_0)}
\]  

(2.7)

where \( F_2^*(\xi, \eta) \) is the complex conjugate of \( F_2(\xi, \eta) \).

Thus, if \( f_1(x, y) \) and \( f_2(x, y) \) are related only by a translation, the inverse Fourier transform of \( Q_{1,2}(\xi, \eta) \) is a pulse which is zero everywhere except nearby
the point of maximum \((x_0, y_0)\), which also gives the displacement between \(f_1(x, y)\) and \(f_2(x, y)\).

Now, suppose \(f_2(x, y)\) is a translated and rotated version of \(f_1(x, y)\), such that:

\[
f_2(x, y) = f_1(cos\theta_0 x + sin\theta_0 y - x_0, -sin\theta_0 x + cos\theta_0 y - y_0).
\]

(2.8)

Given the Fourier transform rotation property we have that \(F_1(\xi, \eta)\) and \(F_2(\xi, \eta)\) are related by:

\[
F_2(\xi, \eta) = e^{-j2\pi(\xi x_0 + \eta y_0)} F_1(cos\theta_0 \xi + sin\theta_0 \eta, -sin\theta_0 \xi + cos\theta_0 \eta).
\]

(2.9)

If we look at the magnitudes \(P_1(\xi, \eta)\) and \(P_2(\xi, \eta)\) of \(F_1(\xi, \eta)\) and \(F_2(\xi, \eta)\), respectively, the following relation holds:

\[
P_2(\xi, \eta) = P_1(cos\theta_0 \xi + sin\theta_0 \eta, -sin\theta_0 \xi + cos\theta_0 \eta)
\]

(2.10)

i.e. the magnitude of the second image is the rotated replica of the magnitude of the second one.

If the coordinates of the obtained magnitudes are transformed into polar coordinates \((\xi, \eta) \rightarrow (\rho, \theta)\), with \(\rho = \sqrt{\xi^2 + \eta^2}\) and \(\theta = \arctan(\eta/\xi)\) we have:

\[
P_2(\rho, \theta) = P_1(\rho, \theta - \theta_0)
\]

(2.11)

and the rotation turns to be a translation \(\theta_0\) in the \(\theta\) coordinate.

Following again the procedure described in the case of pure translation, we can calculate the cross-power spectrum \(\tilde{Q}_{1,2}(\xi', \eta')\) between the Fourier transform of \(P_1(\rho, \theta)\) and \(P_2(\rho, \theta)\). Its inverse Fourier transform will be a pulse like function with its maximum located at the displacement \((0, \theta_0)\).

Similarity measure

In an ideal case the height of the peak would be near one and would be departing from this value for different images. Therefore, in this work we consider the peak

*Except for some minor changes, the procedure described up to this point is the MPOC described and used in [GBC07].
height of the inverse Fourier transform of \( \tilde{Q}_{1,2}(\xi', \eta') \) as the similarity measure for image matching: if two images are similar, their inverse Fourier transform will have a distinct sharp peak, if they are not similar, the peak will drop significantly.

The steps described above give a translation and rotation invariant description and a similarity measure. The procedure could be made more general including scale invariance, performing a Fourier-Mellin transform [CP76]. However, the reference DB specifications are known and during the crime scene analysis all evidence is fully documented within a metrical context, thus scale should not be an issue.

### Spectral weighting functions

In order to enhance the system performance the Fourier magnitudes \( P_1(\xi, \eta) \) and \( P_2(\xi, \eta) \) were multiplied with two different filters, i.e. a high-pass emphasis filter \( H(\xi, \eta) \) and a band-pass function \( W_\beta(\xi, \eta) \).

The high-pass filter [SC96] nulls the contribution of the frequencies around \( \rho = 0 \) that get oversampled due to the Cartesian to polar coordinate transformation. The filter is given by:

\[
X(\xi, \eta) = \cos(\pi \xi)\cos(\pi \eta) \tag{2.12}
\]

\[
H(\xi, \eta) = (1 - X(\xi, \eta)) (2 - X(\xi, \eta)) \tag{2.13}
\]

with \( \xi \) and \( \eta \) between -0.5 and 0.5 (in unit frequency).

The band-pass weighting function [GBC07] has the same shape as the spectrum of a Laplacian of Gaussian (LoG) function and is used to eliminate both high and low frequency components. The filter is given by:

\[
W_\beta(\xi, \eta) = \frac{\xi^2 + \eta^2}{\alpha} \exp \left( -\frac{\xi^2 + \eta^2}{2\beta^2} \right) \tag{2.14}
\]

where \( \beta \) controls the function extension and \( \alpha = 4\pi \beta^4 \) is used for normalization.

We tested the weighting functions separately and together, with different values of \( \beta \), ranging from 50 to 150, in order to find the best performance. Results are shown in Sec. 2.6.
2.6 Results

The RDB was queried to test the performance of the proposed algorithms as well as some of those proposed in literature, both on synthetic and real shoe marks.

In particular we implemented the power spectral density (PSD) algorithm described in [DFR05] and the modified phase only correlation (MPOC) found in [GBC07]∗.

For what concerns our algorithm, it has to be noted that:

- the test with the synthetic shoe marks of set SyntS was performed using both the Mahalanobis distance based algorithm and the Fourier phase correlation (FPC) algorithm outlined in Sec. 2.5.1 and 2.5.2, respectively; however the Mahalanobis method used therein is the one described in [CDC09a], rather than the automated version used in later works†;

- the test using the real shoe marks set RealS was performed using both the FPC and the proposed automatic algorithm based on the Mahalanobis distance map detailed in [DCC09b] and described in Sec. 2.5.1.

2.6.1 Synthetic shoe marks

We first tested the performance of the system when querying the cropped RDB with the SyntS. Results are shown in Table 2.2.

As can be seen from the table, the FPC invariant description performs better than both the PSD and Mahalanobis methods, but doesn’t reach the 100% score of the MPOC algorithm, although the latter is not translation and rotation invariant. Moreover the proposed Mahalanobis system is the worst performer among the compared algorithms.

We then tested the system querying the full shoeprints RDB with the synthetic shoe mark SyntS. The results are shown in Table 2.3.

∗We also tried a SIFT based method [CDC09b] with no success.
†As explained there, the descriptor can be alternatively applied on gray scale shoeprint images either directly or after performing edge detection. During the test we have performed both, and chosen and reported the best match. Thus, in this case results are the fruit of a further non automatic step.
Table 2.2: Results for synthetic shoe marks queried on the cropped shoeprints RDB for the different methods (left column shows the Gaussian noise variance or blur motion displacement). Shown is the percentage of shoe marks that are correctly matched at the first place and in top-five, top-ten and top-twenty rank.

<table>
<thead>
<tr>
<th></th>
<th>Algorithm</th>
<th>PSD</th>
<th>MPOC</th>
<th>Mahalanobis</th>
<th>FPC (Crops)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1 5 10</td>
<td>1 5 10</td>
<td>1 5 10 20</td>
<td>1 5 10 20</td>
</tr>
<tr>
<td>1%</td>
<td></td>
<td>99 100</td>
<td>100 100</td>
<td>100 100 100</td>
<td>95 99 100 100 100 100 100 100</td>
</tr>
<tr>
<td>5%</td>
<td></td>
<td>82 89</td>
<td>93 98</td>
<td>100 100 100 100 78 93 99 99 92 94 95 95</td>
<td></td>
</tr>
<tr>
<td>10%</td>
<td></td>
<td>71 75</td>
<td>82 86</td>
<td>100 100 100 100 74 86 92 98 84 86 87 88</td>
<td></td>
</tr>
<tr>
<td>15%</td>
<td></td>
<td>67 72</td>
<td>74 76</td>
<td>100 100 100 100 – – – – 71 73 76 80</td>
<td></td>
</tr>
<tr>
<td>2 pxl</td>
<td></td>
<td>98 100</td>
<td>100 100</td>
<td>100 100 100 100 100 100 100 100 100 100 100</td>
<td></td>
</tr>
<tr>
<td>5 pxl</td>
<td></td>
<td>95 100</td>
<td>100 100</td>
<td>100 100 100 100 87 98 99 100 100 100 100 100</td>
<td></td>
</tr>
<tr>
<td>10 pxl</td>
<td></td>
<td>60 69</td>
<td>75 79</td>
<td>100 100 100 100 39 74 79 93 100 100 100 100</td>
<td></td>
</tr>
<tr>
<td>15 pxl</td>
<td></td>
<td>68 82</td>
<td>85 89</td>
<td>96 100 100 100 – – – – 95 100 100 100</td>
<td></td>
</tr>
<tr>
<td>20 pxl</td>
<td></td>
<td>34 42</td>
<td>60 74</td>
<td>100 100 100 100 8 38 52 72 98 100 100 100</td>
<td></td>
</tr>
</tbody>
</table>

As can be seen querying the full shoeprints instead of the tiles cropped form them as described in Sec.2.4 causes a degradation of the results, especially when applying motion blur. In Fig. 2.17 the results in the case of a $\sigma = 10\%$ synthetic Gaussian blur are shown in the form of cumulative matching characteristics curves [PMRR00]: the horizontal axis of the graph is the percentage of the reference DB reviewed and the vertical axis is the probability of a match. In Fig. 2.18 the results in the case of a $d = 10$ pxl synthetic motion blur are shown, demonstrating the degradation of the results when the system uses the full prints instead of the tiles.

### 2.6.2 Real shoe marks

We then tested the method employed in this work querying the full shoeprints RDB with the shoe marks coming from the crime scenes. During this test we tried several combinations of the high-pass emphasize filter and the weight function, with $\beta$ values ranging from 50 to 150 in order to obtain the best performance from the FPC method. The cumulative match score results are shown in Fig. 2.19, which
Table 2.3: Results for synthetic shoe marks queried on the cropped shoeprints RDB (left) and on the full shoeprints RDB (right) for the proposed invariant method. Shown is the percentage of shoe marks that are correctly matched at the first place and in top-five, top-ten and top-twenty rank.

<table>
<thead>
<tr>
<th>SyntS</th>
<th>FPC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Crops</td>
</tr>
<tr>
<td></td>
<td>1  5  10  20</td>
</tr>
<tr>
<td>1%</td>
<td>100 100 100 100</td>
</tr>
<tr>
<td>5%</td>
<td>92 94 95 95</td>
</tr>
<tr>
<td>10%</td>
<td>84 86 87 88</td>
</tr>
<tr>
<td>15%</td>
<td>71 73 76 80</td>
</tr>
<tr>
<td>2 pxl</td>
<td>100 100 100 100</td>
</tr>
<tr>
<td>5 pxl</td>
<td>100 100 100 100</td>
</tr>
<tr>
<td>10 pxl</td>
<td>100 100 100 100</td>
</tr>
<tr>
<td>15 pxl</td>
<td>95 100 100 100</td>
</tr>
<tr>
<td>20 pxl</td>
<td>98 100 100 100</td>
</tr>
</tbody>
</table>

Figure 2.17: Results for synthetic shoe marks in the case of \( \sigma = 10\% \) motion blur, queried on the cropped RDB (- -) and on the full shoeprints RDB (—).
shows the best results are obtained when using both the high-pass emphasize filter $H(\xi, \eta)$ and the weight function $W_\beta(\xi, \eta)$, for a value $\beta = 150$.

Once chosen the best combination, we evaluated the employed system in comparison with the other MPOC, PSD and Mahalanobis methods, Fig. 2.20.

As can be seen, the Mahalanobis distance based method is the best performer, followed by the MPOC algorithm (which is performing well for smaller percentage of the reviewed DB) and by the PSD method (which is performing well for bigger percentage of the reviewed DB).

The same graph shows that the translational and rotational invariance has a high price to be paid: analyzing the first 5% of the query results the probability to find the correct shoeprint is 50% for both MPOC and Mahalanobis methods, while it lowers to approximately 17% using the Fourier phase correlation method.

## 2.7 Conclusions

Some systems for the automatic retrieval of footwear that left the shoe marks found at the crime scene was studied. The systems analyzed exploit either the Mahalanobis distance map feature to tackle the noise affecting real shoe marks or
Figure 2.19: Results for real shoe marks as a function of the combinations of the high-pass emphasize filter (HP) and the weight function (LoG(\(\beta\))).

Figure 2.20: Results on real shoe marks for different systems.
the translation and rotation properties of the Fourier transform to realize a translation and rotation invariant system suited for comparison of uncontrolled images.

Several different databases were created:

- a reference DB of cropped shoeprints, a reference DB of full shoeprints;
- a synthetic shoe marks DB created adding Gaussian noise or applying motion blur to the reference DB items;
- a DB with real shoe marks coming from real crime scenes.

The synthetic DB has been tested both on a reference DB of cropped shoeprints, to allow a comparison to the performance of other published systems, and on the full shoeprints, to take advantage of the translation and rotation invariance of the FPC algorithm.

We fine-tuned the system to allow the automatic choice of the Mahalanobis or MPOC algorithm when using the procedure outlined in Sec. 2.5.1, and we tried a combination of weighting functions to use the translation and rotation invariance of the FPC method of Sec. 2.5.2.

Finally, a comparison between some of the methods described in literature, i.e. the power spectral density and the modified phase onli correlation, and those proposed in this work, i.e. the Mahalanobis distance map and the Fourier phase correlation, was made.

Results show that:

- synthetic shoe marks are not a suitable choice to test a footwear retrieval system aiming at finding the sole compatible with the shoe mark found at the crime scene;
- the Mahalanobis distance method coupled with the MPOC method is well performing with real shoe marks, thanks to its robustness to noise; however the system is not invariant for translation and rotation;
- the system performance in the case of the FPC system degrades with the noisy real shoe marks, and its translational and rotational invariance has a price to be paid: analyzing the first 5% of the query results the probability
to find the correct shoeprint is 50% for both MPOC and Mahalanobis methods, while it lowers to approximately 17% using the Fourier based method employed in this work.

Despite the results, the translation and rotation invariance of the system would make it more suitable in real cases, where the uncertainty of the aforementioned parameters would make both the MPOC and the Mahalanobis based systems less effective.

Future work will then be devoted to the study of a suitable pre-processing of the shoe mark images in order to increase the system performance, and other translation and rotation invariant descriptors will be analyzed and included for testing purposes as well.
Chapter 3

Signal restoration with higher order spectra analysis

During evidence collection the first step is always to give a first evaluation of its potential usefulness. Fingerprints, shoe marks, biological evidence and all other crime related material pass a first filtering where the expert chooses if the evidence is worth being collected. This choice can be easily understood: taking all kind of material with no criteria would only result in a large amount of analysis to be done, thus increasing the money and the time spent to complete the processing of the items.

However, sometimes the crime related evidence is the only available and its importance obliges its collection for further analysis and processing with the most recent techniques offered by the research.

One such example is made by long distance photographic material: often intelligence monitoring activities need to be performed far from the scene of interest and the resulting frames suffer problems like camera vibrations and atmospheric conditions.

Moreover the frames are likely to be blurred, due to the time and space variations of the air refractive index, which bends the light rays on their path from the subject of interest to the camera sensor, Fig. 3.1.

A technique based on the the third order spectrum, the bispectrum, has been recently used with good results [Car02, Car03b], although the image suffers an un-
known translation in the origin pixel. This translation uncertainty is always present when using the bispectrum, both for 1D and 2D signals restoration, and needs to be solved on a case by case base.

In this chapter we solve the emergence of this unknown translation in the 1D case, which is the base to solve the same problem in images, i.e. higher dimensional 2D signals.

In Sec. 3.1 a brief overview of the bispectrum usage in different field is given. In Sec. 3.3 we introduce the problem of the appearance of the unknown translation, together with that of phase jumps, which is another related problem which arises in signal reconstruction via the bispectrum; in Sec. ??, we present the details of the problem and the solution adopted, then we continue our report with the results of our experiment on synthetic and real 1D signals in Sec. 3.5 and on 1D simulated turbulent signals in Sec. 3.6. We conclude with Sec. ?? where we outline the future work.

Figure 3.1: Frame of a movie showing a “One Way” road sign, blurred because of air turbulence (movie courtesy of C.J. Carrano).
3.1 Introduction

In this chapter the third order spectrum, simply *bispectrum*, is used. This technique is part of the higher order spectra analysis (HOSA) techniques which allow to reconstruct the phase and magnitude of the Fourier transform of an unknown signal [NP93].

Higher Order Spectra Analysis (HOSA) is a widely used statistical tool that overcomes the drawbacks of standard power spectral analysis, which ignores the phase information of the signal and assumes that the signal is generated by a linear process. HOSA has a reduced sensitivity to additive Gaussian noise [NP93] and preserves the Fourier phase and the magnitude of non-Gaussian signals.

This tool has been applied to several different fields, like the analysis of plasmas [NII+06], the study of interacting oscillators [JSM07], and the estimation of textured surfaces orientation [FK07]. The analysis of the bispectrum of the electroencephalogram waveforms is also used in the proprietary BIS index to monitor the depth of anesthesia [TAB+05].

HOSA is well known for speckle masking removal in astronomy [LWW83] and has also been recently successfully employed to restore images affected by atmospheric turbulence over horizontal and slant paths [Car02, Car03b], combining several frames affected by a different atmospheric turbulence of the same scene.

Figure 3.2: Example of image reconstruction using the bispectrum: in A) the original “cameraman” image is shown, in B) the reconstructed image using 100 frames is shown; note the misplaced origin in B) (images taken from [SRD90]).
However HOSA introduces an unknown translation in the reconstructed signal both in the 1D [CV92] and 2D [SRD90, SG91] cases, thus obliging to further process the restored signals for correction.

In the following a solution to this problem will be showed in the case of a 1D case.

### 3.2 Higher order spectra analysis

The power spectral density is often used in signal processing (we used it also in Chap. 2 for footwear retrieval) where the signal is considered as a superposition of uncorrelated harmonic processes. Thus the signal phase information is not preserved and no other information can be gathered.

On the contrary higher order spectra (sometimes called *polyspectra*) maintain more information and can be useful in three cases:

- to suppress Gaussian noise processes of unknown spectral characteristics in detection tasks, system parameters estimation and classification problems (e.g. see [WFLL07] for an application to image restoration);
- to reconstruct the phase and magnitude of signals (see again [WFLL07] for an application to image restoration);
- to detect and characterize non linear behavior of the signal.

A brief introduction to polyspectra is given in Sec. 3.2.1. For a detailed overview refer to [NP93], which both gives a deeper theoretical analysis and shows some of the applications of higher order spectra analysis.

#### 3.2.1 Higher order spectra: brief theoretical introduction

The \( n \)th order spectrum is defined from the \( n \)th order moment of signal \( x(k) \), where \( k = 0, \pm 1, \pm 2, \ldots \):

\[
m^x_n(\tau_1, \ldots, \tau_{n-1}) = \sum_{k=-\infty}^{+\infty} x(k)x(k + \tau_1) \cdots x(k + \tau_{n-1}).
\] (3.1)
By its definition, moment \( m_n^x(\tau_1, \ldots, \tau_{n-1}) \) gives a measure of the similarity of the signal with its replicas at different translations \( \tau_i \).

More in detail the \( n = 1 \) order moment also corresponds to the mean value of \( x \), while the moment of order \( n = 2 \):

\[
m_2^x(\tau_1) = \sum_{k=-\infty}^{+\infty} x(k)x(k + \tau_1)
\]

(3.2)
gives the signal autocorrelation and corresponds to the signal energy for \( \tau_1 = 0 \).

Starting from the \( n^{th} \) order moment the \( n^{th} \) order spectrum is defined as:

\[
M_n^x(\omega_1, \ldots, \omega_{n-1}) = \sum_{\tau_1=-\infty}^{+\infty} \cdots \sum_{\tau_{n-1}=-\infty}^{+\infty} m_n^x(\tau_1, \ldots, \tau_{n-1}) \times \\
\times \exp -j(\omega_1\tau_1 + \cdots + \omega_{n-1}\tau_{n-1})
\]

(3.3)

Thus the spectrum of order \( n \) is a complex quantity and, as such, can also be expressed in terms of its amplitude \( |M_n^x(\omega_1, \ldots, \omega_{n-1})| \) and phase \( \psi(\omega_1, \ldots, \omega_{n-1}) \):

\[
M_n^x(\omega_1, \ldots, \omega_{n-1}) = |M_n^x(\omega_1, \ldots, \omega_{n-1})| \exp [j\psi_n^x(\omega_1, \ldots, \omega_{n-1})]
\]

(3.4)

The \( n^{th} \) order spectrum of the signal can be expressed in a simpler and more useful way using the Fourier transform \( X(\omega) \) of \( x(k) \):

\[
X(\omega) = |X(\omega)| \exp j\theta(\omega).
\]

(3.5)

In this way the \( n^{th} \) order spectrum of \( x(k) \) can be obtained by:

\[
M_n^x(\omega_1, \ldots, \omega_{n-1}) = X(\omega_1)X(\omega_2) \cdots X(\omega_{n-1})X^*(\omega_1 + \omega_2 + \cdots + \omega_{n-1})
\]

(3.6)

where \( X^*(\omega) \) denotes the complex conjugate of \( X(\omega) \).

This can be rewritten in terms of the amplitude and phase of \( X(\omega) \):

\[
|M_n^x(\omega_1, \ldots, \omega_{n-1})| = |X(\omega_1)| \cdots |X(\omega_{n-1})||X(\omega_1 + \cdots + \omega_{n-1})|
\]

(3.7)

and:

\[
\psi_n^x(\omega_1, \ldots, \omega_{n-1}) = \theta(\omega_1) + \cdots + \theta(\omega_{n-1}) - \theta(\omega_1 + \cdots + \omega_{n-1}).
\]

(3.8)
Two special cases of spectra are worth noting. The first one is the spectrum of order $n = 2$:

$$M^x_2(\omega_1) = X(\omega_1)X^*(\omega_1)$$

which, rewritten in terms of its amplitude and phase, is:

$$|M^x_2(\omega)| = |X(\omega)|^2,$$

$$\psi^x_2(\omega) = 0.$$

thus corresponding to the power spectral density of the Fourier transform of $x(k)$.

The second interesting case is the spectrum of order $n = 3$, called the bispectrum:

$$M^x_3(\omega_1, \omega_2) = X(\omega_1)X^*(\omega_2)X^*(\omega_1 + \omega_2)$$

which, rewritten in terms of its amplitude and phase, is:

$$|M^x_3(\omega_1, \omega_2)| = |X(\omega_1)||X(\omega_2)||X(\omega_1 + \omega_2)|,$$

$$\psi^x_3(\omega_1, \omega_2) = \theta(\omega_1) + \theta(\omega_2) - \theta(\omega_1 + \omega_2).$$

Differently from the $n = 2$ case, the third order spectrum is a complex function with amplitude and phase and, as such, preserves the information stored therein.

### 3.2.2 Bispectrum properties and usefulness

The bispectrum of a 1D signal has some nice symmetry properties so that the knowledge of the bispectrum values in the triangular region:

$$\begin{cases}
\omega_1 \geq 0 \\
\omega_1 \geq \omega_2 \\
\omega_1 + \omega_2 \leq \pi
\end{cases}$$

is enough to have the full information.

In Fig. 3.3 the amplitude of the bispectrum of the 1D signal of Eq. 3.27, used later, is shown. As can be seen the bispectrum of a 1D signal depends on two variables and the knowledge of the bispectrum in the red triangle shown in the
3.2 Higher order spectra analysis

Figure 3.3: Amplitude of the bispectrum of the 1D signal of Eq. 3.27; the red triangle shows the region described by Eq. 3.15.

The same figure is enough to know the behavior of the bispectrum in all the $(\omega_1, \omega_2)$ plane.

Using relations Eq. 3.13 and 3.14 both amplitude and phase of $X(\omega)$ can be obtained from $M^x_3(\omega_1, \omega_2)$. In particular Eq. 3.14 can be rewritten to explicit the dependence of $\theta(\omega)$ on $\psi^x_3(\omega_1, \omega_2)$ and to obtain its value recursively as can be done using the following algorithm [LR82]:

$$\theta(k) = -k \sum_{i=1}^{k} \psi^x_3(i, 1) - k \theta(1) + \theta(0)$$

(3.16)

where discrete frequencies $\omega$ have been used in the previous equation, so that $\omega = \frac{2\pi}{N}k$, with $k = 0, \ldots, N-1^\star$. This method uses only one line of the bispectrum, then $\theta(0) = 0$ while $\theta(1)$ is set arbitrarily, thus choosing arbitrarily the origin of the reconstructed signal.

$^\star$Here $k$ is used as an index, and should not be confused with the $k$ previously used when talking of signal $x(k)$. 
3.3 Translation uncertainty and phase jumps

Several algorithms can be used to reconstruct the phase of the Fourier transform of the original signal (e.g. see Chapter 6 of [NP93]). However many current methods suffer two common problems:

- the translation uncertainty of the reconstructed signal [SG91];

- unwanted jumps of the Fourier phase of the reconstructed signal [CV92].

The first category of pitfalls relates to the fact that to reconstruct the signal from the bispectrum $M^F_{\bar{f}}(\omega_1, \omega_2)$, many current approaches rely to recursive methods which need an initialization constant [NP93]. This constant is chosen arbitrarily, as it is not known, and this generates the translation of the signal to be reconstructed. This is not a problem when the absolute position is not of interest, but is a major problem when there is the need to put together many different reconstructed and related signals, as it can be the case for speckle image reconstruction from a sequence of different frames of the same scene [Car02, Car03b, Car03a].

The second category relates to fake phase jumps of the reconstructed Fourier phase of the signal, Fig. 3.4, which are generally due to the introduction of non integer multiples of $2\pi$ [CV92].

Seemingly, when trying to reconstruct a signal using its bispectrum, at least one of the two aforementioned problems emerge.

3.4 Proposed Method

We perform the reconstruction of the Fourier phase of the signal $f(x)$ with average $\bar{f}$ based on any pair of horizontal consecutive slices of its bispectrum $M^F_{\bar{f}}(\omega_1, \omega_2)$ following [PP98], as this method is suited for a simple yet effective modification. The full signal reconstruction is obtained combining the reconstructed Fourier phase $\theta(\omega)$ with the Fourier amplitude $|F(\omega)|$ (which we consider to be known) of the signal $f(x)$, as this is a requested application in some real cases at least for images [Car02].
3.4 Proposed Method

Figure 3.4: Examples of phase jumps: \( \phi_1(k) \) is the real Fourier transform phase, while \( \phi_4(k), \phi_5(k) \) and \( \phi_6(k) \) are the results of reconstruction using different algorithms (image adapted from [CV92] removing \( \phi_2(k) \) and \( \phi_3(k) \) to enhance clarity).

3.4.1 Phase reconstruction from bispectrum slices

If \( F(\omega) \) is the Fourier transform of the real signal \( f(x) \) and \( M^F_3(\omega_1, \omega_2) \) is its third order spectrum [NP93], the following relation stands:

\[
M^F_3(\omega_1, \omega_2) = F(\omega_1)F(\omega_2)F(-\omega_1 - \omega_2).
\]  

(3.17)

Here \( \theta(\omega) \) and \( \psi(\omega_1, \omega_2) \) are defined to be the phases of \( F(\omega) \) and \( C^F_3(\omega_1, \omega_2) \), respectively. Discrete frequencies \( \omega \) are considered so that \( \omega = \frac{2\pi}{N}k \), with \( k = 0, \ldots, N-1 \).
Following the definition of Eq. 3.17:

$$\psi(k, l) = \theta(k) + \theta(l) + \theta(-k - l). \quad (3.18)$$

Considering the horizontal slices $l$ and $l + 1$ of the bispectrum the result is:

$$\psi(k, l) - \psi(k, l + 1) = \theta(-k - l) - \theta(-k - l - 1)$$

$$+ \theta(l) - \theta(l + 1) \quad (3.19)$$

and setting $m = -k - l$:

$$\theta(m) = \theta(m - 1) + \psi(-l - m, l) - \psi(-l - m, l + 1)$$

$$+ \theta(l + 1) - \theta(l) \quad (3.20)$$

with $m \neq l + 1$.

Expressing the above equation in a closed form, the following is obtained:

$$\theta(m) = \theta(0) + \sum_{n=1}^{m} [\psi(-l - n, l) - \psi(-l - n, l + 1)] + m\theta_0 \quad (3.21)$$

with $\theta(0) = 0$ if $\bar{f} \geq 0$ and $\theta(0) = \pi$ if $\bar{f} < 0$, and $\theta_0 = \theta(l + 1) - \theta(l)$.

Given Eq. 3.18, $\theta_0$ can be written as follows:

$$\theta_0 = \frac{1}{N} \sum_{k=0}^{N-1} [\psi(k, l + 1) - \psi(k, l)]. \quad (3.22)$$

Thus, by combining Eq. 3.21 and Eq. 3.22, it is possible in principle to reconstruct the Fourier phase $\theta(k)$ of signal $f(x)$, knowing the phase $\psi(k, l)$ of its bispectrum.

### 3.4.2 Emergence of the unknown translation

If, as proposed in [PP98], the principal argument of the phase of the bispectrum is used instead of its true phase, an unknown translation constant is inserted. The reason of the translation uncertainty emergence is recalled below.

Let $\tilde{\psi}(k, l)$ be the principal argument of the bispectrum phase $\psi(k, l)$, so that

$$\psi(k, l) = \tilde{\psi}(k, l) + 2\pi I(k, l),$$

where $I(k, l)$ is a function that assumes only integer
values. Using Eq. 3.21 and Eq. 3.22 to evaluate the Fourier phase $\hat{\theta}(m)$ calculated with $\tilde{\psi}(k, l)$ the following is obtained:

$$\hat{\theta}(m) = \sum_{n=1}^{m} [\tilde{\psi}(-l - n, l) - \tilde{\psi}(-l - n, l + 1)]$$

$$+ m \frac{1}{N} \sum_{k=0}^{N-1} [\tilde{\psi}(k, l + 1) - \tilde{\psi}(k, l)]$$

$$= \sum_{n=1}^{m} [\psi(-l - n, l) - \psi(-l - n, l + 1)] + m \theta_0$$

$$- 2\pi \sum_{n=1}^{m} I(-l - n, l)$$

$$- \frac{2\pi}{N} m \sum_{n=0}^{N-1} [I(-l - n, l + 1) - I(-l - n, l)]$$

$$= \theta(m) + 2\pi I_1(m, l) + \frac{2\pi}{N} I_2(l) m$$

(3.23)

where $I_1(m, l)$ and $I_2(l)$ are both integer valued functions.

Using the principal argument of the phase, from last line of Eq. 3.23, it can be seen that $\hat{\theta}(m)$ differs from $\theta(m)$ for two terms: the first one is an integer multiple $I_1(m, l)$ of $2\pi$, whose value depends on $m$ and $l$, while the second one is not an integer multiple of $2\pi$ and depends linearly on $m$.

Thus, the linearly varying term is responsible for the emergence of an unknown phase $(2\pi/N) I_2(l) m$ of the Fourier transform which causes an unknown translation $I_2(l)$ in the reconstructed signal.

If the signal-to-noise ratio (SNR) is high enough to allow to use just a single bispectrum slice $l$, the first term is not a problem, as $\exp(j2\pi I_1(m, l))$ equals one. When the SNR is low, it is possible in principle to reconstruct the phase of the Fourier transform of the signal using several different bispectrum slices $l_j$, and then averaging the results. However this approach should be taken carefully, since making the average can turn a phase difference which is an integer multiples of $2\pi$ into a phase difference equal to a non integer multiple of $2\pi$ and a linear phase component (i.e. the one proportional to $m$) corresponding to an integer signal translation into a linear phase component corresponding to a non integer signal translation.
The first problem can be avoided averaging in the $\exp(j\theta(m))$ domain, but the second one can’t be eliminated and is very sensitive when the SNR is low.

### 3.4.3 Proposed method

In the application under study the the bispectrum is needed to estimate the phase of the signal, thus needs to be calculated.

If $F(k)$ is the Fourier transform of signal $f(x)$, the bispectrum $M^F_3(k, l)$ can be obtained using Eq. 3.17 and then the well known relation:

$$
\psi(k, l) = \arctan \frac{\text{Im}[M^F_3(k, l)]}{\text{Re}[M^F_3(k, l)]}
$$

(3.24)

to calculate its phase.

However, this makes use of the principal argument of the bispectrum, that we are trying to avoid, Sec. 3.3. Thus, the bispectrum phase is calculated solely from the Fourier transform of the signal expressed in polar coordinates.

The modulus and phase of the Fourier transform of the signal are calculated first, i.e. $F(k) = \rho(k) \exp(i\theta(k))$, then the resulting phase $\theta(k)$ is unwrapped and Eq. 3.18 is used to obtain:

$$
\rho^F_3(k, l) = \rho(k) \rho(l) \rho(-k - l)
$$

(3.25)

$$
\psi(k, l) = \theta(k) + \theta(l) - \theta(k + l),
$$

(3.26)

where $M^F_3(k, l) = \rho^F_3 \exp i\psi(k, l)$.

This easy procedure allows to perform the phase reconstruction from all regions with a favorable signal to noise ratio, and to average the results, without the risk of inserting unknown translations or non integer shift in the average signal [PP98].

### 3.5 Results for synthetic and real signals

The proposed method was tested on several different signals composed of both synthetic (Fig. 3.5) and real (Fig. 3.6) signals.
3.5 Results for synthetic and real signals

The synthetic signals used in the tests are:

\[ f_f(x) = 0.8^x \cos(2\pi 0.2x) + 0.6^x \cos(2\pi 0.3x) \]  \hspace{1cm} (3.27)

\[ f_s(x) = 0.95^x \cos(2\pi 0.1x) + 0.8^x \cos(2\pi 0.15x) \]  \hspace{1cm} (3.28)

\[ f_{\sin}(x) = \sin(2\pi 0.02x) \]  \hspace{1cm} (3.29)

\[ f_{\cos}(x) = \cos(2\pi 0.1x) \]  \hspace{1cm} (3.30)

\[ f_G(x) = 10 \exp\left(-\frac{(x - 50)^2}{400}\right) \]  \hspace{1cm} (3.31)

A composite signal \( f_{\text{comp}}(x) \) is used as well, Fig. 3.5.

The real signals are obtained as horizontal slices of a frame (320×256 pixel size) which is part of a movie affected by speckle noise Fig. 3.1. Three slices of this same frame are shown in Fig. 3.6, for horizontal line 50, 100 and 150 (top to bottom).

Assuming both the bispectrum \( M_3^F(\omega_1, \omega_2) \) and the Fourier amplitude \( |F(\omega)| \) as known, the test signal is obtained using the reconstructed Fourier transform phase \( \theta(\omega) \) according to

\[ F(\omega) = |F(\omega)| \exp(j\theta(\omega)). \]
Figure 3.6: Some signals used to test the proposed reconstruction method are the horizontal lines of the frame of Fig. 3.1: A) line 50, B) line 100, and C) line 150.
Figure 3.7: Original (—) and reconstructed (○) signals in case of A) 60 samples synthetic signal and B) 320 samples real signal; the two peaks detail of the 150th horizontal line from Fig. 3.6 is shown in the latter case.

Some of the results in case of synthetic and real signals are shown in Fig. 3.7, where it can be seen that the original (shown as a continuous line) and the reconstructed signal (shown as circles) are superimposed, without any translation difference.

### 3.6 1D turbulence simulation

Here the adopted solution is tested on simulated 1D turbulent signals in order to restore the original 1D signal, showing that the proposed solution could be well suited, once extended to 2D, for the restoration of images affected by air
turbulence.

If the 1D signal $f(x)$ to be acquired at a distance is corrupted by the 1D atmospheric turbulence response $h_i(x)$, which depends on time $i$, the acquired signal at that same time $i$ is:

$$g_i(x) = h_i(x) * f(x),$$  \hfill (3.32)

and taking the Fourier transform the relation becomes:

$$G_i(k) = H_i(k)F(k).$$  \hfill (3.33)

If $F(k) = |F(k)| \exp(j\theta(k))$ and $M^G_{3i}(k, l)$ is the bispectrum of $G_i(k)$, the signal amplitude and phase can be reconstructed as follows [Car02, Car03b]:

$$|F(k)|^2 = \frac{\langle |G_i(k)|^2 \rangle_i}{\langle |H_i(k)|^2 \rangle_i},$$  \hfill (3.34)

$$\theta(k + l) = \theta(k) + \theta(l) - \arg[\langle M^G_{3i}(k, l) \rangle_i],$$  \hfill (3.35)

where $\langle \cdot \rangle_i$ denotes the time average of the signal.

The last recursive equation has the same form of Eq. 3.18, thus can be solved using the horizontal slices method, once $\arg[\langle M^G_{3i}(k, l) \rangle_i]$ is used to express $\psi(k, l)$.

The simulation is as follows:

- the test signal is replicated 50 times;
- a family of 50 Gaussian curves are generated randomly, the only limit being the standard deviation lower than 10 samples;
- each replica of the signal is convolved with a different Gaussian;
- the signal resulting from each convolution is regarded as being a different turbulent 1D signal $g_i(x)$.

Then the proposed method is used to restore the original 1D signal starting from its turbulent 1D versions.

Results are shown in Fig. 3.8 in the case of the 150th horizontal line, Fig. 3.6.C, for different values of the maximum standard deviation of the Gaussian family used to simulate the turbulence. As can be seen, the signal is well reconstructed.
Figure 3.8: Reconstruction results in case of 1D simulation of turbulence for a maximum Gaussian standard deviation of A) 5, and B) 10 samples. Circles are used for the reconstructed signals. Panel C) is the same of panel B), with two simulated turbulent signals superimposed for reference.
when the $h_t(x)$ maximum standard deviation value is 5 samples, Fig. 3.8.A, and it is slightly different for a maximum standard deviation value of 10 samples, corresponding to a FWHM of approximately 23 samples, Fig. 3.8.B. In Fig. 3.8.C two simulated turbulent signals are shown to demonstrate the degree of degradation introduced with the Gaussian curves convolution.

3.7 Conclusions

Higher order spectra analysis can be used to restore a corrupted signal but suffers from an unknown translation that shifts the signal origin. A simple solution is given here in the case of 1D signal using bispectrum slices and avoiding coordinates transformations.

The proposed method was tested and demonstrated on synthetic and real signals, and on simulated 1D atmospheric turbulent signals.

The next step will be to generalize the approach to the forensically interesting field of image restoration when corrupted by air turbulence.
Chapter 4

Chemical imaging of human fingerprints

In this chapter the results of the research on human fingerprint analysis are shown [Yu05]. Human fingerprint deposits were studied using the facilities available at the synchrotron line Sincrotrone Elettra at Trieste [Elete].

Sample fingerprints were produced and analyzed with several different techniques:

- Fourier transform infrared microspectroscopy (FT-IRMS);
- x-ray fluorescence (XRF);
- x-ray absorption spectroscopy (XAS);
- x-ray phase contrast microscopy (XPC);

To evaluate the feasibility of a complete characterization of the fingerprint composition to give comprehensive information to the investigators.

Among the techniques cited above, FT-IRMS proved to be the most useful and promising. Thus a system for the chemical imaging of the fingerprint was studied to allow the full automatic chemical mapping of the functional groups in the deposited marks.
4.1 Introduction

Forensic science already benefits from synchrotron radiation (SR) sources: up to now there have been reports on synchrotron reflectance infrared microspectroscopy used for the fast nondestructive study of inks on paper [WPM+02], and in forensic trace evidence analysis [MNKM02, KKSC05]. Synchrotron radiation has been also employed in glass fragments analysis [NNT+06, NNM+06] and more recently in white paint fragments investigation [NWS+09]. A proposal to employ x-ray diffraction for lipsticks analysis in forensic science was also reported [ASS07].

Infrared microspectroscopy with standard laboratory sources has been used to analyze particles and droplets that constitutes fingerprint ridge deposits [WSB04]: sample fingerprints were deposited on purpose on aluminum coated slides before and after washing the hands to produce normal, sebaceous and eccrine fingerprints*. A functional group analysis was performed in the attempt to distinguish between adult and children fingerprints, with partial success.

In [GWHM05] four different substances (Ibuprofen, Vitamin C, Non-Dairy Creamer, and Sweet’N Low) were handled by the donors before depositing the test fingerprints on a gold plated glass. A microscope was then used to find the particles which were analyzed with infrared microspectroscopy to recognize the handled materials. In this work both a standard and a synchrotron source were employed, and the second one proved to be better suited to analyze smaller particles due to its brightness over standard laboratory sources [CRW95].

More recently a study looked for exogenous substances in fingerprints using a standard laboratory source [NWTR09]. Fingerprints were first washed and then rubbed on the face, neck and hair to produce sebaceous rich fingerprint which were deposited on metal oxide coated glasses and silicon windows. The fingers were contaminated with cocaine and PETN (an explosive) before fingerprint deposition and the authors tested different spectral comparison algorithms to find the best performing one.

*Normal fingerprints are produced simply touching the surface with fingers of the unwashed hands, while sebaceous and eccrine fingerprints are produced washing the hands and rubbing the forehead and the breast, respectively.
4.2 Experimental setup

Several human fingerprints were deposited on lightly doped silicon wafers and poly-ethylene-terephthalate (PET)*. The prints were left by male and female donors in depletion series, i.e. the same finger was left more than once in order to provide a richer and poorer version of the same finger, Fig. 4.2. Two different deposition modalities were adopted:

- a set of normal fingerprints, deposited without any particular procedure, Sec. 4.3;

*Although not representative of the typical forensic evidential sample, these material were chosen because they are well suited for experiments.
Table 4.1: List of the contents found in fingerprints; note the different contribution of eccrine, apocrine and sebaceous glands (table taken from [CLMS04]).

- a set of fingerprints heavily contaminated by a different mixture of gunshot residues, Sec. 4.4.

The two different sets were used in order to analyze and test the developed imaging methods in two common forensic science scenarios.

### 4.3 Uncontaminated fingerprints

The FT-IR microspectroscopy (FT-IRMS) technique was used to realize the chemical imaging of uncontaminated fingerprints deposited on silicon substrates, in order to characterize the chemical nature of the deposits. The FT-IRMS measurements have been carried out at the SISSI beamline of Elettra [Elete].
4.3 Uncontaminated fingerprints

Figure 4.2: The fingerprint were left in depletion series, i.e. the same finger was left more than once in order to provide a richer (n. 1) and poorer (n. i) version of the same finger. Each fingerprint was also divided in two for parallel analysis with different techniques.

4.3.1 Fourier transform infrared microspectroscopy

Infrared spectroscopy exploits the absorption of the light at specific frequencies, which are characteristic of a given chemical bond. Because of this, infrared spectroscopy detects, distinguishes and determines the relative amount of nucleic acids, fats (lipids), and proteins.

The technique employed in FT-IRMS exploits an interferometer like the Michelson interferometer depicted in Fig. 4.3. A source of light $S$ emits radiation which is sent to a beam splitter (diagonal dashed line in figure) placed in the middle of the configuration. The splitted beams travel to two orthogonal mirrors $M_1$ and $M_2$ which reflect them back. The beams are superimposed again by the beamsplitter
Figure 4.3: Scheme of a Michelson interferometer: FT-IRMS uses a similar working principle, where $S$ is a broad band frequency source, $D$ is the detector, $M_1$ and $M_2$ are two mirrors and the diagonal dashed line in the middle is a beam splitter, used to generate two separate rays walking along two paths of different optical length (image taken from [HG84]).

(this because they now come from different directions) and sends them to the detector $D$, which records the phase difference accumulated by the two beams on their paths. If a material to be analyzed is placed on the path of one of the split beams, $D$ will record different intensities depending on the position $x$ of the moving mirror $M_2$ and on the frequency of the beam. If a broad band source is employed and the path of one of the rays is modified changing the mirror position $M_2$, a signal like the one shown on the left of Fig. 4.4 will be produced.

The signal produced by the interferometer is related to the spectrum of the material under analysis by a transform; thus taking the Fourier transform of the output a spectrum like the one on the right of Fig. 4.4 will be obtained.
4.3 Uncontaminated fingerprints

Figure 4.4: The output of the FT-IRMS (left) is Fourier transformed to produce the spectrum of the investigated material (right), which results fully characterized in the frequency range under study (image taken from [HG84]).

4.3.2 Experiment setup

The samples have been prepared by leaving fingerprints on silicon substrates following a precise pattern of depletion. Each donor has to leave his fingerprint for eight consecutive times creating an impoverishment scale.

FT-IRMS spectra have been collected in the Mid-IR regime from 4000 to 500 cm\(^{-1}\) using a Bruker Vertex 70 Fourier Transform interferometer equipped with a blackbody source. The infrared beam is sent to a Hyperion 3000 infrared microscope equipped with 15x cassegrain optics. Light is detected in transmission mode by a single-element Hg-Cd-Te detector, cooled with liquid nitrogen. Using knife edge apertures and motorized stage we collected chemical maps by defining a matrix of points of \(100 \times 100 \ \mu m^2\). Morphologically characterized zones of fingerprints are then chemically characterized assembling maps of the collected spectra.

Data are acquired by averaging either 256 scans per point, or 512 scans per point if the sample is particularly poor, at a frequency resolution of 16 cm\(^{-1}\).

4.3.3 Chemical mapping

Thus each picture element is not characterized by a unique intensity value, but by a full spectrum in the same frequency range mentioned above, Fig. 4.6. The data collected by the FT-IRMS must be analyzed to visualize the chemical maps of the compounds of interest [HG84, GH85a, GH85b]. This analysis can be performed
Figure 4.5: Available methods for extracting distribution maps; ANN: artificial neural network, CLS: classical least squares, LDA: linear discriminant analysis, MCR-ALS: multivariate curve resolution-alternating least squares, OPA: orthogonal projection analysis, PCA: principal component analysis, PLS: partial least squares, PMF: positive matrix factorization, SVM: support vector machine. Refer to [GRC08] for a detailed analysis (image taken from the same source).

following a multivariate or an univariate approach, Fig. 4.5.

The first case takes into account the whole spectral information contained in the data; several analysis methods are available, ranging from factor analysis (which model the data as a linear combination of terms and noise) to clustering techniques (where spectra are grouped as they share some features). See [GRC08] for a detailed overview of the multivariate approach.

In the second case the chemical bonds of the compound under investigation are considered responsible of the system response, as could be the case for the 1655 cm$^{-1}$ C=O stretch frequency of Amide I. The map is then built either considering the signal intensity at a given wavelength or calculating the area under a specific spectral peak.
4.3 Uncontaminated fingerprints

<table>
<thead>
<tr>
<th>Frequency (cm(^{-1}))</th>
<th>Vibration</th>
</tr>
</thead>
<tbody>
<tr>
<td>3281</td>
<td>N–H stretch (secondary amide)</td>
</tr>
<tr>
<td>1741</td>
<td>C=O stretch (saturated ester)</td>
</tr>
<tr>
<td>1655 (highlighted)</td>
<td>C=O stretch (secondary amide)</td>
</tr>
<tr>
<td>1546</td>
<td>Major: N–H in-plane bend (secondary amide)</td>
</tr>
<tr>
<td></td>
<td>Minor: C–N stretch</td>
</tr>
<tr>
<td>1463</td>
<td>CH(_3) asymmetric bend</td>
</tr>
<tr>
<td></td>
<td>CH(_2) symmetric bend</td>
</tr>
<tr>
<td>1379</td>
<td>CH(_3) symmetric bend</td>
</tr>
<tr>
<td>1233</td>
<td>C–N stretch (secondary amide)</td>
</tr>
<tr>
<td>1160</td>
<td>C–C–O stretch (saturated ester)</td>
</tr>
<tr>
<td>1113</td>
<td>O–C–C stretch (saturated ester)</td>
</tr>
</tbody>
</table>

Table 4.2: Characteristic frequencies and vibrational modes of a particle found in an eccrine fingerprint; highlighted are the interesting frequencies (table taken from [WSB04]).

Since we know the rough wavelength position of the peaks of interest we chose the univariate analysis and functional group mapping since more representative of the chemistry of the sample.

More in detail, following internal tests and results available in literature [WSB04], we chose to use the frequencies in the 1700–1500 cm\(^{-1}\) range, Tab. 4.2.

The selected frequencies correspond to the vibrational modes of:

- Amide I group: 1600–1700 cm\(^{-1}\) range, mainly due to C=O stretching, slightly coupled with CN stretching, CCN deformation and and NH bending;

- Amide II group: around 1550 cm\(^{-1}\), due to the N–H bending coupled with CN stretching.

### 4.3.4 FT-IRMS data processing

The collected information needs subsequent processing: once selected a window of wave numbers of interest (e.g. from 1700 cm\(^{-1}\) to 1500 cm\(^{-1}\)), the spectrum needs to be corrected for its baseline contribution and vertical displacement.
Chemical imaging of human fingerprints

Figure 4.6: The FT-IRMS beam line acquires a spectrum for each pixel of the sample.

We don’t use rubber band or scattering baseline correction [Bru10], rather we prefer to estimate the baseline as a polynomial of order $n$ whose coefficients $a_i$ are found through the minimization of non-quadratic cost functions [MCB+05], chosen between the symmetrical (or asymmetrical) truncated quadratic and a Huber function. While the $a_i$ are calculated by the optimization procedure, the polynomial order has to be fixed manually. In our case it was enough to choose $n = 4$ to have good results. This procedure is repeated for each spectrum which is then baseline corrected by simple subtraction of the calculated polynomial before proceeding with the fitting procedure explained below.

Each baseline corrected spectra is modeled as a sum of Gaussian functions with different center frequencies $k_i$ and standard deviation $\sigma_i$. Differently from the baseline fitting polynomial order choice, we can’t choose from the beginning the number of Gaussians to be fitted to the baseline corrected data, as some of the spectra show only one Gaussian and others have up to six contributions. Thus we developed an automatic procedure to determine the number of Gaussian components to be used in the fit.

The system is based on what we called a peak look up table (PLUT) which create a precise correspondence between the first, second and third derivative signs (i.e. plus or minus) and the occurrence of a possible peak. The PLUT identifies the candidate peaks in each spectrum thus allowing the automatic choice of the
number of Gaussian curves to be used for the fit.

To sum up, each spectrum is modeled as follows:

\[ y(k) = a + \sum_{i=1}^{n} b_i k^i + \sum_{i=1}^{m} c_i \exp \left( \frac{(k - k_i)^2}{2\sigma_i^2} \right), \]  

(4.1)

where \( a \) is the baseline offset (extracted from the polynomial for convenience), \( b_i \) the polynomial coefficients, \( n \) its order, \( m \) the number of fitting Gaussians and \( k_i \) and \( \sigma_i \) their center and standard deviation, respectively.

Finally, the fitting step is made twice:

- in the first run the peak positions are calculated with the lookup table and are used as known parameter to evaluate the other fit parameters, i.e. the \( c_i \) and \( \sigma_i \), Fig. 4.7;

- in the second run all parameters are initialized with the values calculated in the previous step and the Gaussians centers \( k_i \) are limited to vary in a fixed range \( \Delta K \), Fig. 4.8.

The results of the described procedure can be seen in Fig. 4.9, where a more difficult spectrum is shown, demonstrating the ability of the proposed algorithm to fit complex chemical systems.

### 4.3.5 Data processing interface

In order to ease the automatic processing of large amount of data, an interface was studied to load, analyze, configure and show the spectra acquired with the FT-IRMS.

In Fig. 4.10 one of the possible interface is shown. The left part allows to see and inspect the spectra and their fit. The right part is dedicated to settings and facilities like:

- data matrix dimensions;
- fit parameters variation;
- integral map range;
Figure 4.7: During the first fitting step the spectrum (×) is processed with the lookup method to identify the number and positions of Gaussian maxima (○); these values are considered fixed in this first step.

- peak map value and variation;
- save and load results.

### 4.3.6 FT-IRMS results

Once found the Gaussians center frequencies $k_i$, standard deviations $\sigma_i$ and heights $c_i$, they can be attributed to the functional groups of interest, in our case Amide I and Amide II.

With this information two different chemical maps can be obtained:

- an *integral map* showing the total contribution of the chemical species in the selected frequency range of 1700–1500 cm$^{-1}$;
- a *peak map* or *functional group map* for each functional group, to identify the contribution of each one without the risk of mistakes.
4.3 Uncontaminated fingerprints

Figure 4.8: During the second fitting step the spectrum (×) is fitted considering all parameters variable in a determined and chemically supported range; note the positions of Gaussian maxima estimate din previous step (○) are different from the maxima found at the end of the procedure, as demonstrated by the colored Gaussian components drawn below the spectrum.

In fact, a common mistake emerges when in the need of mapping a particular frequency region where a different functional group has a strong signal. If interested in the contribution at 1550 cm\(^{-1}\), the spectrum of Fig. 4.11 would mask the signal with the much stronger functional group active around 1600 cm\(^{-1}\).

This is shown for clarity in Fig. 4.12. Panel A) shows the integral map obtained summing all contributions to the spectrum in the range 1565–1535 cm\(^{-1}\). As can be seen a high signal is present; however this is the pixel where the spectrum of Fig. 4.11 is located. Panel B) shows the map built considering the functional group, i.e. built with the value of the height of the Gaussian centered at 1550 cm\(^{-1}\) as a result of the automatic fitting procedure. As a result the fake strong signal of Fig. 4.12.A is no more present in Fig. 4.12.B, which correctly shows the contributions due to that frequency.

Thus, thanks to the proposed method, the acquired sample fingerprints were characterized both via their morphology and their content, either as an integral
Figure 4.9: More complex spectrum analysis example: once removed the baseline the first fitting step identifies the number and position of Gaussian components, A), then execute the fit allowing the parameters to vary in a limited range, B); the spectrum data (×) with the superimposed fit (—) and the resulting Gaussian components are shown in panel C).
4.4 Contaminated fingerprints

Figure 4.10: The interface for automatic spectra processing allows to load the spectra acquired with the FT-IRMS, set the fit parameters, fit automatically all spectra and build the integral or functional group maps.

information or as a functional group representation, as shown in Fig. 4.13.

4.4 Contaminated fingerprints

For the contaminated fingerprints we employed X-Ray Fluorescence (XRF), X-ray Absorption Spectroscopy (XAS) and phase-contrast microradiography. The main features of third generation synchrotron radiation sources as the one employed in this work are the high intensity and spatial coherence of photons emitted in a small solid angle. This allows to work with short acquisition times tuning the photon energy to study specific sample features and giving the possibility to apply novel techniques in forensic science [KRR^05].
Figure 4.11: Trying to estimate the contribution of functional groups around 1550 cm$^{-1}$ would result in a fake signal, due to the important contribution of the group centered around 1500 cm$^{-1}$.

### 4.4.1 X-ray fluorescence and X-ray absorption spectroscopy

For both XRF and XAS an 80 mm$^2$ silicon drift detector has been used (KETEK GmbH AXAS-M) with an energy resolution < 160 eV FWHM at the Mn K$_\alpha$ line. These measurements have been carried out at the XAFS beamline of Elettra [DAM+09].

The gunshot residue contaminated fingerprint was firstly analyzed by XRF for a qualitative elemental characterization. Fig. 4.14 shows the energy dispersive XRF spectrum of the contaminated fingerprint using an excitation energy of 14270 eV. The peaks with a higher count rate corresponding the X-ray emission of the most abundant elements are labeled in Fig. 4.14. The presence of lead as well as of copper and zinc can be related to gunshot events, as these elements can be found in gunshot residues [DBB10].

In order to characterize the chemical state of the most abundant contaminants in the fingerprint, X-ray absorption spectra were recorded, in fluorescence mode, at the Pb L3 edge (13035 eV), Cu K-edge (8979 eV) and Zn K-edge (9659 eV). Since the gunshot residue contaminated fingerprint was deposited on PET, which
Figure 4.12: The integral map obtained summing all contributions to the spectrum in the range 1565–1535 cm$^{-1}$ is shown in A), while the functional group map representing the group centered at 1550 cm$^{-1}$ is shown in B) as a result of the automatic fitting procedure; note the fake strong signal in A) is no more in B).
Figure 4.13: A fingerprint can be characterized with its morphology and chemical content: A) fingerprint under study, B) integral map in the range 1700–1500 cm$^{-1}$, C) functional group map for the 1600 cm$^{-1}$ wavenumber.
4.4 Contaminated fingerprints

Figure 4.14: Energy dispersive XRF spectrum of the contaminated fingerprint using an excitation energy of 14270 eV.

is X-ray transparent at the energies at which the XAS measurements have been performed, a metallic foil of Pb, Cu, and Zn could be measured in transmission mode simultaneously to the spectra recorded on the fingerprints.

Fig. 4.15 shows the absorption spectra recorded at Pb L3, Cu K, and Zn K edge, panel a), b), and c) respectively. The spectra relative to the fingerprints (shown as ◦) are compared to those relative to the corresponding metallic elements. The spectra at the Cu and Zn K-edge present features that are similar to those of the spectra of the corresponding metals although a dumping and a frequency shifts of the oscillations can be observed. The XAS data recorded at Pb L3 edge show completely different features with respect to the metallic Pb. An analysis of the derivatives of the normalized absorption (not shown in figure) evidences an energy shift of the onset of the absorption of 2.6 eV with respect to the metallic Pb. It is plausible to assume that lead in the contaminated fingerprint is in an oxidized state.
Figure 4.15: XAS spectra of a) contaminated fingerprints at Pb L3 edge, b) Cu K-edge and c) Zn K-edge. The spectra (○) are compared to the spectra of the corresponding metals (–).

4.4.2 Phase-contrast microradiography

Synchrotron X-ray imaging experiments have been performed at the SYRMEP beamline at Elettra [TLA+10]. The source is a bending magnet and the beamline provides, at a distance of about 23 m from the source, a monochromatic, parallel, laminar-section X-ray beam with a maximum area at sample of approximately 160 × 6 mm². The monochromator is based on a double silicon crystal system working in Bragg configuration and the energy of the X-ray beam can be tuned between 8.3 and 35 keV with an energy resolving power on the order of 10⁻³, caused by the natural divergence of the beam. The detector used is a water-cooled CCD camera (Photonic Science VHR, 4008 × 2672 pixel, full frame, 12 bit, effective pixel size 4.5 μm) coupled to a gadolinium oxysulphide scintillator placed on a fiber optic coupler.

The high spatial coherence of the X-ray synchrotron beam allows to apply the phase-contrast technique, which is very well suited to image samples with low absorption with respect to hard X-rays, such biological systems [SSK+95, CBB+96]. It has been demonstrated that the fine interference structure of phase-images allows detecting very small density and morphological variations in the sample giving contrast in regions of a highly localized change in the refractive index of the specimen. The radiograph is then an outlined image of those domains,
4.4 Contaminated fingerprints

Figure 4.16: X-ray phase contrast microradiographs of a portion of the same fingerprint recorded at different sample to detector distances $D$; from left to right: 45 mm, 200 mm and 500 mm.

while the absorption imaging shows a strongly limited absorption contrast leading to lower signal to noise ratio. In this case we use free space propagation and the phase effects are visible simple increasing the sample to detector distance $D$.

Fig. 4.16 shows a portion of a fingerprint measured at different $D$ values in order to visualize and optimize the phase-contrast effects. It can be observed that increasing the distance $D$ the details of the image become sharper and the fingerprint contrast increases. Fig. 4.17 shows the image of a whole fingerprint obtained at $D = 500$ mm.

To obtain the map of deposition of a given chemical element inside the sample, dual energy microradiography can be used. Several microradiographs are recorded just above or below the absorption edges of these elements. As an example, an image recorded below the L3 edge of lead is presented in Fig. 4.18.

We propose to use monochromatic radiation at two energies close to the absorption edge of a given chemical element in order to obtain the precise localization of that element in the observed fingerprint sample [KRR+05]. This is possible by repeating the measurements both below and above the absorption edge, and by subtracting (in the logarithmic domain) the first image from the latter.

To obtain the map of deposition of the given chemical element inside the sample from the differential images, five images should be acquired for any investigated sample area:

- two images of the irradiated sample, so called “sample images”, at the wavelengths above and below the absorption edge;
Figure 4.17: Phase contrast microradiograph of a contaminated fingerprint; due to the laminar shape of the X-ray beam (6 mm high in the vertical direction), the image of the whole fingerprint has been obtained combining several radiographs recorded at different vertical positions of the sample; exposure time for each radiograph 0.7 s, $D = 500$ mm.

Figure 4.18: Phase-contrast radiograph of a fingerprint taken at 12.975 keV, i.e. just below the L3-edge of Pb (13.035 keV); exposure time is 0.7 s, $D = 200$ mm.
4.5 Conclusions

Here is reported the first attempt to combine several different analytical techniques to describe fingerprints not only in terms of their morphology, but also in terms of their endogenous and exogenous content.

An algorithm to automatically analyze the different functional groups was proposed and tested, showing the ability of the system to correctly map the organic content of fingerprints overcoming the mistakes introducing by a simpler integral mapping approach.

A combination of X-ray fluorescence, X-ray absorption and X-ray phase contrast imaging, was used to analyze the gunshot residues contamination in fingerprints, allowing to find some element of interest.

These techniques were tested as alternative imaging techniques to be used in order to both preserve the collected items and to allow fingerprint analysis in those cases where all the other classical techniques fail. Moreover, this approach has the potential to give a broader spectrum of information pertaining the crime, i.e. not only the morphology of the fingerprint, but also its organic compounds and contaminants content.

While being in its early stage, the above work seems promising in helping investigators to visualize and analyze latent, i.e. not visible, fingerprints.
Conclusions

This thesis work has been devoted to the development of new methods and applications for forensic sciences. Image and signal processing have a lot to offer to forensic science and this work proves that they can give a valuable help during evidence analysis and interpretation:

**Footwear retrieval** A system for the automatic retrieval of footwear was setup and tested in order to find the make and model of the shoe sole that left its mark on the crime scene. A novel algorithm based on the Mahalanobis distance map was proposed and tested on both synthetic and real shoe marks coming from crime scene. A comparison made with some of the works available in literature showed that the propose system performs well, although it still suffers for not being translation, rotation and scale invariant. Future research will be devoted to invariance and to increase the number of items in the real shoe mark database.

**Signal reconstruction** A simple approach to 1D signal reconstruction based the third order spectrum was developed. Differently form other works, the systems doesn’t introduce unknown translation in the restored signal and is suitable for average in all cases with a low SNR. Although interesting *per se* this system needs to be extended to image, i.e. to 2D, to fully reveal its potential in the restoration of atmospheric turbulence for intelligence purpose.

**Fingerprint imaging and mapping** Fingerprints were analyze in an unconventional manner: using the analytical facilities of a synchrotron source we studied the morphology and chemical composition of fingerprints. An FT-
Conclusions

IRMS technique was used to acquire hyperspectral images of the fingerprints organic compounds; a procedure and an interface were elaborated to automatically map the functional groups contribution of the various components, thus allowing errors introduced by wrong integration procedures. A gunshot residues analysis was performed using X-ray based techniques showing some elements of interest. Future research will be devoted to refine the FT-IRMS analysis, in order to extend the analysis from functional groups to full chemical compounds in order to extend fingerprint mapping to substances forensically more interesting.

Publications, conferences and other activities

Here follows the list of articles, conference participations and other activities worth noting as part of this PhD research.


- F. Cervelli, and S. Carrato: “Signal reconstruction using bispectrum without translation uncertainty”, in 7th Image and Signal Processing and Analysis


Conclusions


- F. Cervelli, F. Dardi, and S. Carrato, “A texture recognition system of real shoe marks taken from crime scenes” in Proc. IEEE International Confer-
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