Content Based Information Retrieval in Forensic Image Databases

by

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ABSTRACT

This thesis gives an overview of the various image databases that are available, and ways of searching these databases on image contents. The developments in research groups of searching in image databases is evaluated and compared with the forensic databases that exist. Forensic Image databases of fingerprints, faces, shoeprints, handwriting, cartridge cases, drugs tablets and tool marks are described.

The developments in these fields appear to be valuable for forensic databases, especially that of the framework in MPEG-7, where the searching in image databases is standardized. In the future, the combination of the databases (also DNA-databases) and possibilities to combine these can result in stronger forensic evidence. Stronger algorithms for feature selection are necessary, and it is expected that human interaction will be necessary for a long time.

SAMENVATTING

Keywords: forensic science, contents based information retrieval, image databases, correlation algorithms

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Dedication

This thesis is dedicated to my parents and grandmothers, without whom none of this would have been even possible.

CONTENTS

Figures and Tables

0 Preface

This thesis is composed out of five peer-reviewed publications in journals. The text of the articles is included and where appropriate updates are given, however the layout is in a standardized form.
The next articles have been combined:

- Introduction (altered form): Pattern Recognition in Forensic Image Databases, Journal of Forensic Science, accepted July 2001, to be published March 2001.
- Geradts Z, Keijer J, Keereweer I . A New Approach to Automatic Comparison of Striation Marks. 1994; 39(4): 974-980. New developments in the field of 3D-measurement have been added.
- Geradts, Z; Keijzer, J ; The Image database REBEZO for Shoeprints with developments on automatic classification of shoe outsole designs, FORENSIC SCIENCE INTERNATIONAL, (15 SEP 1996) Vol. 82, No. 1, pp. 21-31
- Geradts, Z; Bijhold, J. Hermsen, R, Murtagh, F; Image matching algorithms for breech face marks and firing pins in a database of spent cartridge cases of firearms, Forensic Science International 2001, June 2001, Vol. 119, No. 1, pp. 97-106.
- Geradts, Z; Bijhold, J; Poortman, A, Hardy, H; Databases of logo's of Drugs Pills – submitted to Journal of Electronic Imaging

A summary of this thesis with more information on image processing has also been submitted to Science and Justice. Most information has also been published in a modified form in the SPIE-Proceedings.

Ik denk er over om ook het gait-artikel toe te voegen als dat geaccepteerd is.

The introduction (in modified form) will be published in the Journal of Forensic Science in March 2001.

1 Introduction

In forensic science the importance of image databases is known for years. The successful use of databases for fingerprints[1] is an example of a very useful database. However, many suspects know that they can be caught on fingerprints and take precautions. Nowadays we see that DNA-databases[2] [3] are important in solving even old crimes. Other databases (e.g. Shoeprints, tool marks, handwriting, cartridge cases and bullets) are also important to use in casework. If evidence is used in combination with other facts or evidence, the relevancy of the evidence will get even better. The research in image databases and forensic databases is a rapidly changing field, as it will directly improve the number of cases that is solved.

In the 20th century many databases where available in paper files or photographs (e.g. cartridge cases[4] were available in photographs). In the 80s we saw that the fingerprint databases[4] were the first to be widely used in networks. Furthermore, there were efforts of the Bundes Kriminal Amt to store images of handwriting in a database. These databases were all in binary image format. In the beginning of the 90s we saw that computer databases of shoeprints, tool marks and striation marks on cartridge cases and bullets[23] were available. All these databases need fast and accurate automatic comparison algorithms.

The different aspects of an image should be covered. In forensic science, this means that it has to be known which parts of the images are important for a forensic scientist for finding correspondence in images. Then, knowledge of information retrieval, visual data modeling and representation, pattern recognition and computer vision, multimedia database organization, man-machine interaction, psychological modeling and data visualization are needed for developing a system working properly.

The use of databases of images in forensic science can have multiple advantages:

- Crimes are solved based on technical evidence (e.g. if a bullet is found at the scene of crime and someone is arrested in possession of a firearm in a different place, this might result in a “cold” hit if the striations match)

- By using the databases statistical information is available on how unique a certain feature is. As in fingerprints, in the beginning of the 20th century there were 8-16 points needed for a match (depending on the country[5]). Due to statistical ranking in these databases, we now have more information about the uniqueness of fingerprints, and the number of points versus the statistical relevancy. If a new kind of evidence (like the shape of ears) is introduced, these databases are even more valuable, since it is just the expert who draws conclusions based on experience. The databases will result in more objective results in forensic examination. One problem is that it takes lots of time to fill these databases and draw conclusions on these statistics.

1.1 Main Contributions

In this research, we are evaluating how the different algorithms for correlation and image matching are applicable in forensic science. First an overview will be given of current research and applications.

Several methods of comparison are tested on practical forensic image databases. The brute force-approach is one of them, and we compared this to other methods that are available. This study is a work of ten years research at the forensic institute. First the databases of toolmarks and shoeprints are handled in this research. Then the databases of cartridge cases and bullets are described. The last database that has been studied is a database of drugs pills. The work resulted in some new approaches for the comparison of images in forensic image databases. It is meant to give an overview of the methods that can be used for these databases, in such a way that forensic scientists have a better insight in the procedures and methods that have been implemented in these databases.

Based on our experience with these databases and study from literature, we will conclude with final remarks.

1.2 Outline of this thesis

Here, we briefly describe the outline of the thesis and the contents of each of the chapters.

Chapter 2 gives a short overview of the state of the art in contents based retrieval. It is not intended to give a complete overview of the literature available.

We continue in Chapter 3 with correlation methods for toolmarks, then chapter 4 will handle the shoeprints, chapter 5 the cartridge cases and chapter 6 the drugs pills. Each of the chapters 3-6 will cover experiments with the various methods for correlation. The conclusions are given in chapter 7.

2 State of the Art

Many organizations (also other than forensic science institutes) have large databases and video collections in digital format that they would like to have accessible for on-line access. With the development of digital photography and video equipment, we see an explosion in the number of images and video sequences that are stored in digital format. For this reason, the field of contents based retrieval has emerged as an important area in computer vision and image processing.

In the field of image databases in general many research groups are active. Databases of faces, logos and other shapes are well known (QBIC[6], Photobook and Virage).

The variety of knowledge required in visual information retrieval is large. Interaction with visual contents should permit the searching for visual data referring directly to its contents. Elements such as color, shape, texture and color and the higher-level concept of the meaning of objects in the scene are clues for retrieving the right images in the database.

Different types of information are associated with images and video[7].

1. Data that is not directly concerned with image/video contents, but in some way related to it (suspects name, place where crime happened etc

2. Data, which refers to the visual contents of the images. Two levels are possible:

    - Data may refer to intermediate level features such as color, shape, spatial relationship, texture and their combinations (content-dependent metadata).

    - Data may refer to contents semantics. This is contents-descriptive data. It is concerned with real-world entities such as emotions and meanings associated with the contents

2.1 Types of databases

In literature[7] databases are divided in different generations. In this research we will focus on second-generation databases.

2.1.1 First generation visual information retrieval systems

In first generation visual information retrieval systems, the images are linked in the database, and can be searched by meta-data. The text strings are stored and can be searched in a structured way, as in classical SQL-databases.
With text descriptors there are several limitations:

- The text descriptors depend on what the user enters in the database. Different users might enter different text descriptions in the database on a certain image, and even the same user might enter a different text the next time

- Several image features, such as texture and color distribution, are difficult to describe in text descriptors for a user

It takes much effort for the user, and if the classification rules change, all images have to be classified again

An example of this method is classifying the shapes of a shoeprint by visually determining which shapes are visible (e.g. circles, triangles etc) by means of a classification scheme.

2.1.2 Second generation visual information systems

In second-generation visual information systems, there are different ways of searching in the database. The user can search in the database on features as texture, shapes and color distribution. The features can be combined with text strings in the database. With this method the user can search for a certain group of cases in a forensic database (e.g. restricted on an area) and compare the images with features of the images.

For these second-generation visual information systems, there are two options:

- Similarity search: the images database is ranked based on the most similar images to a certain chosen image. Often in these kinds of systems there is user interaction: the user will work on relevance feedback, by either chosen a different image in the database as a sample, or by selecting a different feature, or modifying the weight of certain features.

- Matching: in this process the user just receives the images that match, and does not receive anything else then that.

For searching, these systems often are divided in subsystems, which index the images, and do pre-processing of images for selecting the most relevant features.

Most research nowadays focuses on finding features in images, indexing a database in an efficient manner and the man-machine-interface. Furthermore searching in 3D-databases and video-databases is an area that gets more attention in literature[8]

2.1.3 Third generation visual information systems

These systems work in an “intelligent” manner, as the Human Visual System work. The system learns from previous examples, and will draw conclusions based on experience. These systems are not yet in commercial systems. For forensic databases these systems might draw conclusions themselves. The development of these systems depends very much of the understanding of the human visual system combined with acceptance by the users.

2.2 Visual Content

The current databases focus on visual content[9] [10]. In this section a short overview is given of perceptual features of video and images. These are features as color, texture, shape and motion.

2.2.1 Color

Color reflects to the chromatic attributes of the image as it is captured with a sensor. There are different geometric color models (usually three-dimensional) that are used. They allow the discrimination between colors stimuli and permit similarity judgment and identification. Color histograms are the most traditional way of describing the low-level properties of an image.

Often users also describe the colors by their names. However there are differences in the way that people translate colors in their names, e.g. color can be important in a database of drugs pills or a database of child pornography images.

2.2.2 Texture

Texture is a term that is used for differences of brightness in an image. It often works with high frequencies in the image spectrum. From the psychological point of view, texture features are granularity, directionality and repetitiveness. It is difficult to express texture in words. It is often described in numerical vectors. Texture is a feature that can be used in a database of striation marks or impression marks.

2.2.3 Shape

Shapes are object identities in a meaningful form. Some shape features are expressed in text, e.g. squares, rectangles and circles. However more complex forms of shape are more difficult to express in text.

In the traditional way a shape is expressed through a set of features that are extracted with image processing tools. Features can characterize either the global form of the shape – such as area, local elements of its boundary or corners, characteristics points etc. In this approach shapes are viewed as points in the shape feature space. For calculating the degree of similarity of two shapes, standard mathematical distances are used.

Often preprocessing is needed for finding the shapes in an image. Multiple scale techniques for filtering the shapes from the image are often used as filters.

The property of invariance – this means that a shape representation in the database is invariant to geometric transformations as scaling, rotating and translation- is important in the comparison of shapes. Often shapes have to be extracted by human interaction, since it is not always known beforehand which shapes are important in an image. Shapes are important for logos of drugs pills.

2.2.4 Structure

The image structure is defined as a set of features that provide the "gestalt" impression of an image. The distribution of visual features can be used to classify and retrieve an image. A simple example is distinguishing line drawings from pictures by deriving a set of edges, corners and their location in image space. The structure can be important for a fast pre-selection of a database (selecting a part of the database), based on the contents. An example is searching in handwriting by means of the structure in a database.

2.2.5 Spatial relationships

The spatial entities are shapes as lines, regions, point and objects. The position of the shapes in the image and their direction are used for matching the spatial relationship.

2.2.6 Motion

Motion is used in video databases and is analyzed in a sequence of frames. There are several models for calculating the motion vectors in video database. These methods can either be very simple, as calculating the difference between two images, and determining the motion, or more complex with optical flows and non-linear equations. Motion can be implemented in a database of gait of persons for forensic use.

2.2.7 Content semantics

The content semantics depends very much on the field of the forensic database. For fingerprint databases other models or standards will be used as for firearms. They have to be implemented in a database with interaction with experts.

2.3 Similarity Models

These are models for finding the similarities in images. Often these are based on histograms of a feature in the image.

2.3.1 Metric model

This model is frequently used for databases of features, since it is easy in the implementations. There are several distance functions commonly used[11]: the Euclidean distance, the city-block-distance and the Minkowsky distance for histograms. However several studies in psychology have pointed out that the human visual system has some inadequacies compared to this system. The earthmover's distance[12] is a new kind of implementation that is more equivalent to the human visual system.

It appears that this model is often used, since it is easy in its implementation, and efficient indexing methods are possible. In pattern recognition many feature-extracting methods are implemented and available, and this makes this method easy to use with these methods.

This method can also be used in combination with virtual metric spaces, if there is no representative feature of visual entity. This method is used in interaction with experts that is represented in a point in a virtual space.

2.3.2 Other models[13]

The feature contrast model of Tversky defines similarities according to set-theoretic considerations. Similarity ordering is obtained as a linear combination of a function of two types of features: those that are common to the two stimuli and those that belong only to one of them. This model does not allow for easy indexing.

Transformational distances are also used[14]. This approach is based on the idea that one shape is transformed through a deformation process. The amount of deformation is a measure for the similarity. There are models with elastic models that use a discrete set of parameters to evaluate the similarity of shapes. There are also evolutionary models that consider shapes as the result of a process in which at every step, forces are applied at specific points of the contours. Image registration methods are used in this model. Indexing with this method is very complex.

2.4 Indexing methods

If the number of images in a database is large, there is a need for indexing visual information to improve the speed of searching in the database. This is similar to textual information, where classic indexing methods as hashing tables are employed.

If the visual properties – e.g. Color, texture, shape are modeled as points in a feature space, points access methods (PAM) developed for spatial data can be used. The performance of these methods depends on the number of features used and the distance measures that are used. Furthermore, in image databases often there is a need for searching on image features based on a weight factor.

2.5 Performance

In document retrieval[15], the performance is measured using the table (if the ground truth is known):

	Relevant	**Not Relevant**
Retrieved	**Correctly retrieved**	**Falsely retrieved**
Not retrieved	**Missed**	**Correctly rejected**

We have the recall and precision measures for evaluating the performance of a database.

Recall = $\frac{relevant\_correctly\_retrieved}{all\_relevant}$

Precision = $\frac{relevant\_correctly\_retrieved}{all\_retrieved}$

However in these cases one needs to know the ground truth. Other aspects are also important, such as:

- Average number of examples needed to obtain a certain degree of satisfaction
- Average number of iterations to obtain a satisfactory result
- Computational Complexity

Often the recall is visualized in a graph with recall vs. percentage of the database.

As in all recognition applications the construction of a test set is an important problem. There exist numbers[16] of database that can be used for testing the performance in databases. NIST has developed databases for faces and fingerprints.

Two significant goals are required in image databases[17]: accuracy and efficiency. There are not many benchmarks available, however in forensic research, we see for faces, fingerprints and cartridge cases efforts have been made by the users.

The performance criteria depend on the “ground truth”. In most forensic databases the “ground truth” is clear, since this should be the fingerprint of the person, or the marks made with the same firearm.

The basic idea behind the matching process is that the most relevant images should be on top position. In this regard we might find use in recall of a database: the number of images retrieved / the total number of images that should be retrieved in top position. Since often the images are not in the top position of the database another measure is the percentage of images of the database that should be compared manually before all matches with the ground truth are found.

2.6 Image databases

The human ability to recognize objects involves perception and associating the resulting information with one or a combination of more than one with its memory contents. Visual perception leans deriving information from a specific scene. The actual process of the human brain is not known[18], however several models exist of the formation of the image on the retina and the mental processing of the projected image. A short overview of these methods is given, since there are many similarities in the matching process with biometric databases and databases of objects.

Several research groups try to design machines that emulate human abilities. The current results[19] are far from successful. Dividing the human abilities in smaller tasks and implementing them reveal promising results.

The biometric systems are an important area of research for these systems, and in history form a basis for the modern image database. For these systems a biometric measure is used for identifying a person of authenticating the person. For the biometric systems there are several requirements: [20]

1. Universality: each person should have the characteristics.
2. Uniqueness: indicates that no two persons should have the same characteristics.
3. Permanence: the characteristics should not change in time.
4. Collect ability: the characteristics can be measured.

These systems might serve two goals: identification or recognition[21]. The identification is the most difficult one to achieve.

Examples of biometric signs are fingerprints, palm prints, DNA, iris, face and speech.

If we look into the fingerprint systems, the Henry Classification scheme[22] is often used. This scheme is useful for efficient manual classification, since humans can easily identify each class. AFIS-systems most often try to implement this classification scheme, however other approaches have been realized.

2.6.1 Fingerprints

Figure 1 : Example of finger print image

Four major approaches have been taken for automatic fingerprint classification [23]:

1. Syntactic: the ridge patterns and minutiae are approximated as a string of primitives/ the pre-defined classes are modeled as a set of grammars from the training samples. When a new pattern arrives the string of primitives are formed and passed to a parser whose output yields the class of the input pattern.
2. Structural: features based on minutiae are extracted and then represented using a graph data structure. Exploiting the topology of features does structural matching. The use of topology of singularities is another approach.
3. Neural network approach: the feature vector is constructed and classified by a neural network classifier. There are several approaches for the feature vectors that are used.
4. Statistical approaches: statistical classifiers are used instead of neural classifiers.

In the matching process there are two approaches: point matching and structural matching. In point matching, two sets of minutiae code using their locations are aligned and the sum of similarity between the overlapping minutiae is calculated. The similarity between two minutiae is measured using the attributes of the minutiae. In point matching alignment is an important problem, and for that reason a registration method is needed. In structural matching, the locations are discarded, and a graph, which codes the relative locations of minutiae, is constructed and compared.

For determination of the minutiae it appears that there is a lack of reliable minutiae extraction algorithms. These algorithms result in spurious minutiae. They can be caused by scars, over-inking and sweat or by the algorithm itself. For this reason most often human intervention is needed after using these algorithms.

2.6.2 Faces

Faces are easy to obtain with a camera, and are important for the surveillance industry. The problem with face recognition in a random system is that the faces are not acquired in a standardized way. The face can be in any position; the lighting and magnification can be different. Furthermore, hairstyles, beard or stubbles, makeup, jewels and glasses will all influence the appearance of a face. Other longer-term effects on faces are aging, weight change and facial changes, such as scars or a face-lift. For police investigation often there are also images that are taken under more standardized conditions.

First of all the face should be recognized in the image[24]. The requirements of these algorithms for commercial applications are that they work fast, which can be realized in hardware. After this normalization is necessary to correct them for positioning. Furthermore, it is necessary to find the position of the face in the image. This can be handled by determining the position of the nose and eyes.

For face recognition systems to perform effectively it is important to isolate and extract the main features in the input data in the most efficient way. The elements of such a representation can be made in a wide variety of ways, and it depends on the task which approach will be appropriate.

One of the main problems with face recognition is dimensionality reduction to remove much of the redundant sampling[25]. Sophisticated pre-processing techniques are required for the best results.

There are several methods for feature-based approaches. It requires the detection and measurement of salient facial points. There exist approaches in which the primary facial features such as eyes, nose and mouth are represented in an economic space based on their relative positions and sizes. With this approach important data of the face may be lost[26], especially if shape and texture variations are considered as an important part of the features of a face.

To locate facial key-points, automatic feature finding algorithms have been developed. The problem with this approach is that in low-resolution data accurate identification and positioning of small facial areas in very difficult.

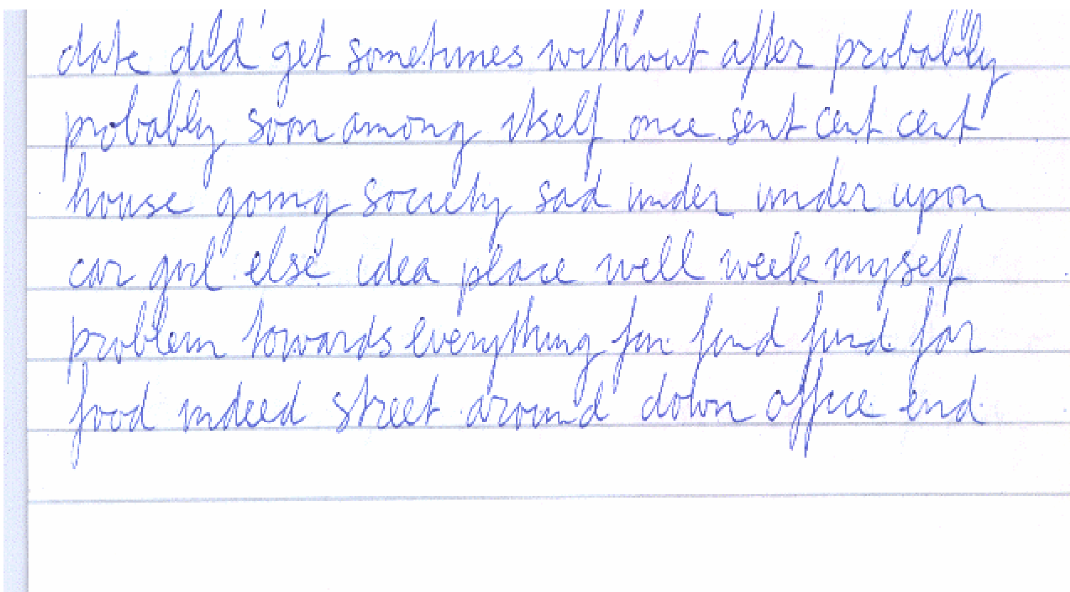
Template matching involves the use of pixel intensity information. This can be in the original grey-level dataset or in pre-processed datasets. The templates can be the entire face or regions corresponding to general feature locations, as mouth and eyes. Cross correlation of test images with all training images is used to identify the best matches. Often other measures are needed as alignment and filtering to achieve the best results.

As with fingerprints the statistical approaches can also be used. Principal Components Analysis (PCA[27]) is a simple statistical dimensionality reducing technique that is often used for face recognition. PCA, via the Karhunen-Loève transform can extract the most statistically significant information for a set of images as a set of eigenvectors (often called 'eigenfaces'). Once the faces have been normalized for their eye position, they can be treated as a one-dimensional array of pixel values, which are called eigenvectors. The most significant eigenvectors can be chosen and compared. This is also possible in combination with a neural network. The eigenface method is not invariant to image transformation as scaling and shift. An approach to compensate for variations in illumination are Gabor filters[28].

Matching the images can be done with a simple correlation of image vectors. Also neural networks have a long history of being used for face recognition, however computational limitations restrict the amount of testing. Many different implementations of neural networks have been implemented[29].

2.6.3 Handwriting

For forensic handwriting comparison different systems[30] exist on the market. The oldest



system is the Fish-system, which is developed by the Bundes Kriminal Amt in Germany. Another well-known system is

Figure 2: Example of handwriting

Script, developed by TNO in the Netherlands. In both systems handwriting is digitized with a flatbed scanner and the strokes of certain letters are analyzed with user interaction The script system measures for each image: inter-line distance, and the inter-word distance. For each word all letter heights are measured, the slant and the word width. For Fish also the black/white statistics is computed, and they will analyze upper and lower loops if available. These systems are used for threatening letters and analyzing who might have written these letters.

2.7 References

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3 Experiments with databases in Practice

In the next chapters we will test the different kinds of databases on databases in practice. The first example is striation marks, and is the simplest from algorithmic point of view. After that the shoeprints are based on shapes. Much effort is given to impression marks of cartridge cases of firearms. The last database is drugs pills in which much research of MPEG-7 developments has been implemented.

4 Databases of Tool marks

This chapter has been submitted 27 september 1993, and has been accepted 10 December 1993 for the Journal of Forensic Science.

“A new approach to Automatic Comparison of Striation Marks”
Geradts Z, Keijer J, Keereweer I . A New Approach to Automatic Comparison of Striation Marks. 1994; 39(4): 974-980. New developments in the field of 3D-measurement have been added , which have also been published in the SPIE-proceedings of Investigative Image Processing.

4.1 Introduction

Tool marks are often found at the scene of crime. They can appear in a wide variety of shapes depending on the tool and the surfaces where the tool mark is formed. Often pliers, screwdrivers or crowbars are used for entering a building for a burglary. These tools will cause tool marks that appear in different shapes: striation marks and impression marks. In several police regions in the Netherlands the images of the tool marks that are found at the scene of crime are stored in a database, and when a suspect has been found with tools, test marks are made with these tools and compared with the database. In Figure 3 an example is shown of a striation and impression mark in a police database.

The tool marks in the database are created by a procedure. A casting is made with a gray silicon casting material, and subsequently these images are stored in the database. The database is used for pre-selection, and subsequently the real tool mark is compared with a test mark of the tool on a comparison microscope by a qualified examiner.

In this research we focus on striation marks, since they are most time-consuming for an examiner making a comparison. The tool can have many different angles to the surface, and for each angle a different striation mark is formed. For this reason the examiner has to make several test striation marks with different angles of the tool. In the case of a screwdriver, the examiner will make at least four test striation marks under different angles for each side of the screwdriver. All of these test marks have to be compared with the striation marks.

Striation marks are caused by irregularities in the upper part of the blade of the screwdriver when scraping off material of a surface that is softer than the tool itself. If the irregularities in the upper part of the blade of the screwdriver are damaged or have grinding marks these can be characteristics of the tool that has been used. Depending on these damages and grinding marks, and the quality of the tool mark itself, a qualified examiner can conclude that the blade of the screwdriver has caused the striation mark.

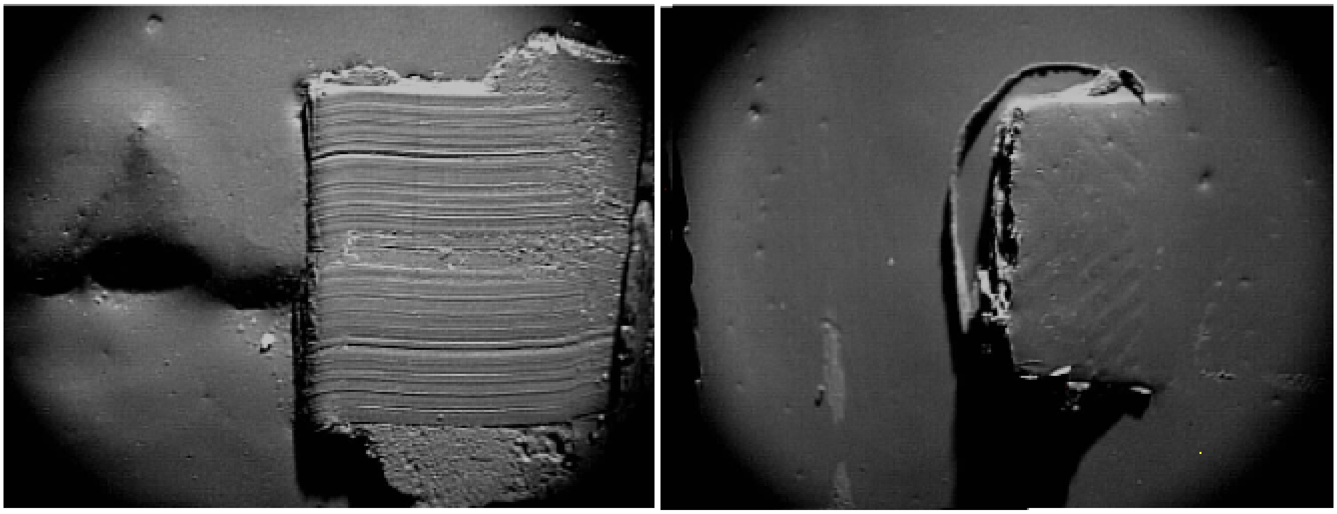

Figure 3: Tool marks in database. Left: striation mark; right: impression mark.

A difficulty with forensic examination is that the tool mark found at the scene of crime might be partial. In this case the striation mark should be matched to the test striation mark. Furthermore the screwdriver could be damaged in the meantime because it has been used, and this will cause the striation marks to differ. Also the striation mark can be (partially) zoomed because of stretch or shrinkage of the material (e.g. elastic deformation) in which the tool mark has been formed. And finally the angle as shown in Figure 4 might also give a gradient in the tool mark.

Figure 4: Example of angle of screwdriver and influence on the striation mark. Furthermore a partial striation mark is visible in this image.

In the past[1] we have developed a comparison algorithm that takes all these variations into account. In this research the method for taking a signature that has to be compared to the database is improved. Furthermore we focus on the structured light approach.

4.2 Side Light

Dull surfaces, such as the gray casting material reflect light with the same intensity in all directions[2]. Diffuse reflection is sometimes also called Lambertian reflection because Lambert's is used to calculate the intensity of the reflected light. Lambert's law states that the intensity of the reflected light is proportional to the cosine of the angle è between the light vector L and the surface normal N (Figure 5).

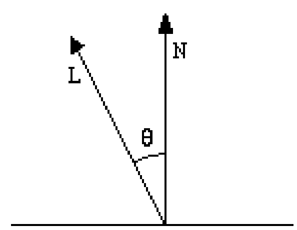

Figure 5: Lambert's law; the angle è between the light vector L and the normal N determines the intensity of the light reflected from the surface.

Lambert's law can be formulated as

$$I = I_p k_d \cos q \qquad (1)$$

I_p is the color of the light source and k_d, the diffuse-reflection coefficient, is a material property varying between zero and one. The angle q must be between 0° and 90°. The surface will otherwise be directed from the light source and shadowed. The direction to the observer is irrelevant since the light is reflected equally in all directions from the surface.

If both N and L are normalized, the equation can be simplified by computing cos è as the product of N and L:

$$I = I_p k_d N \bullet L \qquad (2)$$

We can see that we very much depend on the light condition in this approach. For this reason under different light circumstances or light variations due to the surface itself, the striation mark might appear differently.

This is one of the reasons to choose for an approach using 3D images. The method that we used is the structured light approach. With this method it is possible to acquire a 3D-image in a few seconds. This method is faster than the implementations of laser triangulation methods16 that scan a surface that we have tested in the past.

4.3 Comparison Methods

In the literature some studies have been made on automatic comparison of striation marks on bullets. Further Katterwe and Deinet[3][3] have published on the statistics and comparison of striation marks. A recent development of an algorithm was from Uchiyama[4][4].

On the commercial market there are developed two systems for automatic comparison of striation and impression marks. Drugfire[5][5] is developed for the FBI for cartridge cases and the other system is Bulletproof for bullets and cartridge cases. A patent application[6][6] from Bulletproof was published for the automatic comparison algorithm of striation marks on bullets. This system works with pre-selection based on signatures from bullets.

Automatic comparison of impression marks is in this research not further studied, since with this kind of comparison much more information has to be compared. For the user it is also most convenient to have an automatic comparison on striation patterns first, since this costs much more time to compare. One comparison of a striation mark with a tool takes at least 16 comparisons, since a variation of the angle of the tool with the surface will result in another striation mark.

4.3.1 Acquisition of the signature

In our research it appeared that from a good quality striation mark a vertical line of gray-values could be sampled. In Figure 6 a sampled line from a striation mark is shown. The vertical line is magnified 50 times in the horizontal direction. This line (signature) appears to be characteristic for the striation mark.

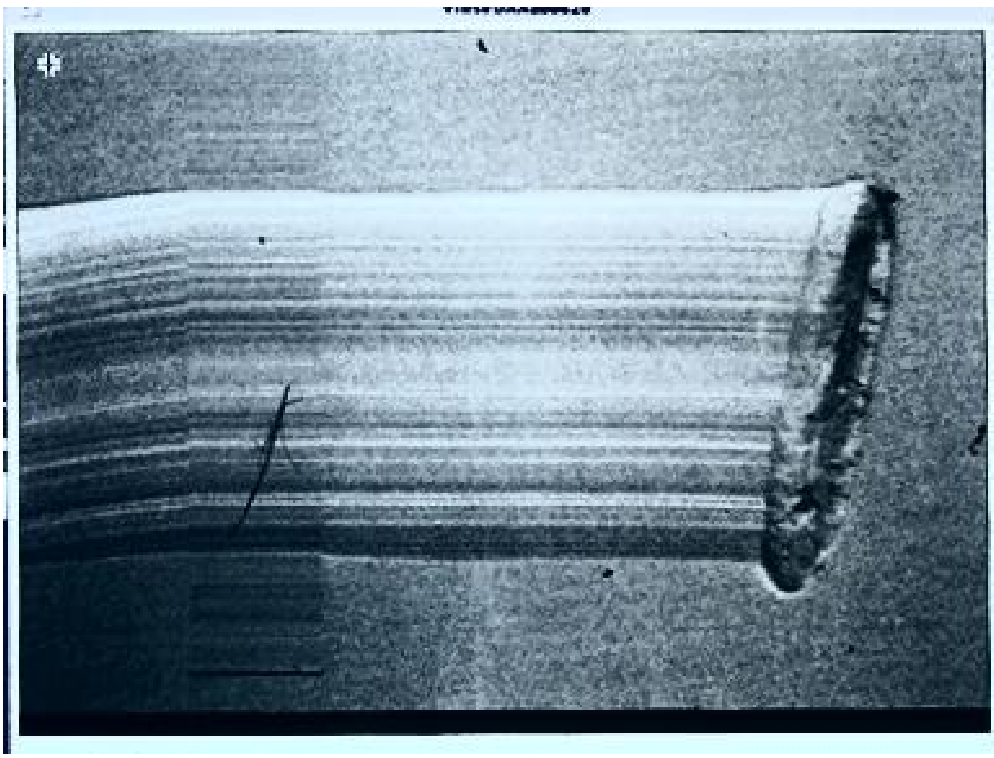

Figure 6: Sample of one vertical line out of a striation mark. The line is magnified 50 times horizontally

In the case shown in Figure 6 a good quality striation mark is shown. Since most striation marks do not have this quality, N vertical lines are averaged in an area pointed by the user. The average of the gray-values is computed by:

$$\bar{g}_x = \frac{\sum_{x=0}^{x=n}\sum_{y=0}^{y=N} g_{n,\,x_{y\pm 1}}}{N}$$

Equation 1

Where

g(x) : average signature

g(n,x) : gray value on line n and position x

N : number of lines

For the correction of the angle and variation between the lines in a matrix a correction is applied. This correction compares a shift of one pixel with the value of the next line.

Since the light distribution is also important, a calibration is made with a gray surface of a cast. A high frequency filter is used to compensate the spikes and noise in the gray values.

4.4 Correlation methods

In the literature many different methods are described. Most often the B/W-approach is used by simplifying the striation marks as bar code and then comparing the bar codes. Some experiments have been done for this approach, but it appeared to be difficult to determine what part of the striation mark is black and what part is white. To get reproducible results this would require a very high level of standardization. For this reason the comparison of the gray values is selected.

In the first approach the cross-correlation function was computed [7[7]]. This method seemed to be useful for comparing the striation marks. The power spectrum can be obtained from the Fourier transform of the ring data function, since

$$P(f) = R \otimes R^*$$

Equation 2

where

$$R = \bar{g}_x$$

and R^* is the complex conjugate of R.

This method of obtaining the power spectrum is practicable because of the speed of the FFT-algorithms. Since computing the cross-correlation can compensate for the shift of lines it is computed as the inverse transform of the complex cross-power spectrum of the two striation signatures.

$$j_{12} = F^{-1}[R_1 \otimes R_2]$$

Equation 3

The method that is often used for comparing striation marks on bullets is correlation. This method is only applicable to whole striation marks. For our algorithm a kind of correlation function is computed using the equation:

$$r_k = \frac{\sum_{n=1}^{N}(x_n - y_n)^2 - (s_x - s_y)^2}{N s_x s_y}$$

Equation 4

where

ρ : coefficient

x : gray values from signature of striation mark of scene of crime

y : gray values from signature of test mark

N : number of data points per striation mark

μ : mean of gray values

σ : standard deviation of gray values

The correlation coefficient will be 0 if the two patterns match exactly. In practice this will never the case, since there will always be slight differences between two striation patterns. Computing the mean of the gray values compensates for fluctuations in intensity between the different images.

In our experiments this resulted for tool marks made with the same screwdrivers not in very good results. Since this was often the case a partial comparison was computed, by sampling a part of the data. This also reduces the time necessary for computing.

For this reason a shift was introduced in the algorithm, so the minimum value of the shifts is determined.

Since a screwdriver can have many positions in relation to the surface, there is a need for a small local zoom-compensation. In Figure 7 the method of zooming is shown. In a matrix of 1x3 the gray values of the two signatures are compared. If a shift of one pixel is in three comparisons better for the difference in gray values, this shift will be made. Statistics of the number and directions of the shifts are computed, since they might be fluctuating in one striation mark.

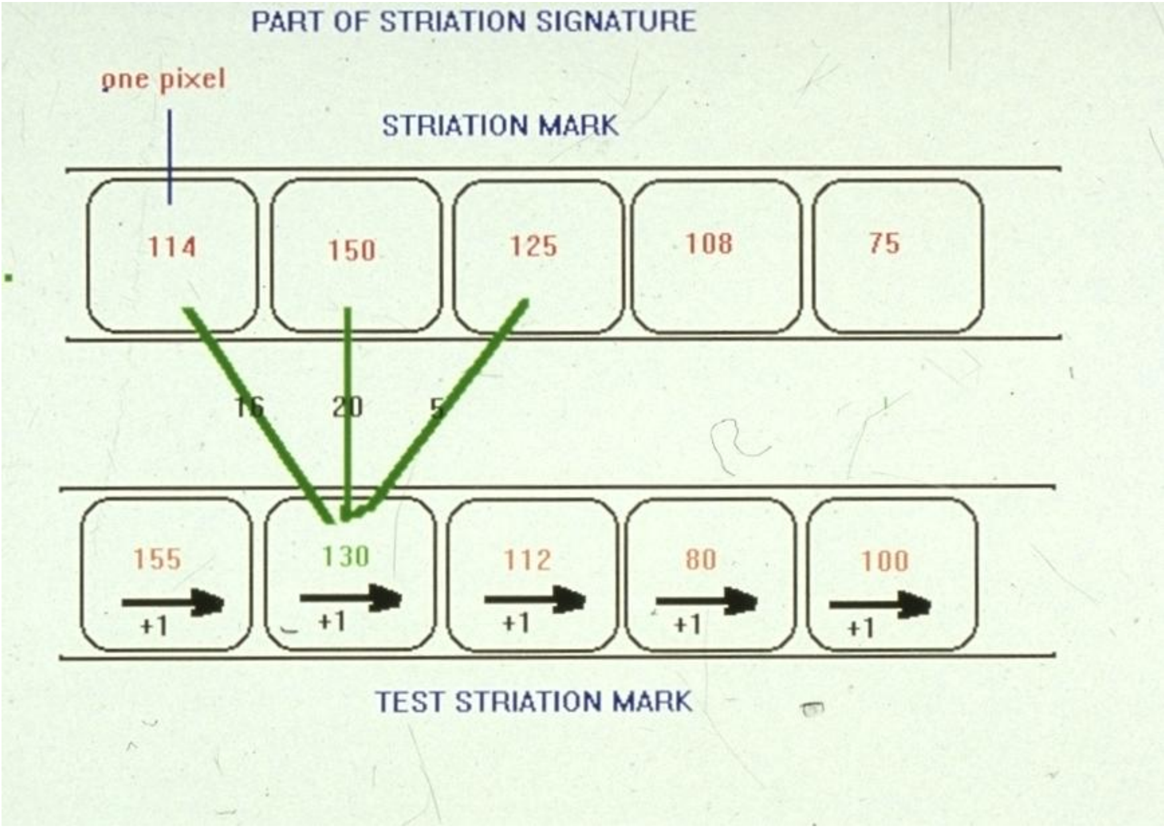

Figure 7 : Adaptive zoom

The results of the correlation coefficient and the statistics of the shift are handled by fuzzy rules. These rules will give the final result.

In our experiments it appeared that the comparison algorithm works well for good and deep striation patterns.

Since faster pre selection algorithms are necessary there are some more pre selection steps:

- Main frequencies in the striation mark by FFT;
- Averaged contrast comparison;
- Partial pre-selection.

It appears that with a combination of those techniques a better and faster pre selection of the striation marks is possible.

4.5 Conclusions

The pre selection of tool marks will work well for good and deep striation marks. For striation marks that do not have a good quality, it is better to use an interactive system in which the user determines if the signature is characteristic for the striation mark.

For this system standardization is very important. If the standards are not used, the pre selection will give bad results. Since a striation mark is 3-dimensional and it is visualized 2-dimensional, it might be better to use 3D-acquisition techniques. Moiré-interferometry and laser-stylus are planned to be tested in future research.

4.6 3D-acquisition : Structured light approach

The structured light system is similar to the passive stereovision system with one camera replaced by a projector. A light source projects a vertical plane of light that creates narrow stripes on the scene. Since the intersection of an illumination plane of known position and a line of sight determines a point, the 3D-location of all points along that illuminated stripe that are visible by the camera can be obtained from a single image. For dense reconstruction the scene must be accurately scanned and many images should be taken.

High reliability identification of light planes with minimal assumptions on the nature of the scene is achieved by sequentially projecting several patterns. A robust and widely applied structured light system is based on spatio-temporal modulation has been described by Kato[8]. Gray codes are used to label light planes, and each illumination pattern represents one of the bit planes of the Gray code labels.

In our approach we used the structured light system of OMECA[9] that is based on this research. In this system lines are projected on the surface by means of a micro mirror device that can be operated by the computer. The system consists of a CCD-camera, a frame grabber and a computer that will control the stripes that are projected, and calculate the depth of the surface. The advantage of the micro mirror projector compared to the LCD-projector is that we have a higher light intensity and that the pattern itself has more contrast. The method implemented will also cover problems with dark places of the object. In the apparatus is shown as used in our laboratory. With this method it is possible to measure a striation pattern with a precision of several microns[10].

Figure 8 : **OMECA structured light equipment**

4.7 Correlation algorithms

For the correlation of tool marks several methods are described in literature[11] [12] [13] [14]. In the past we have also examined if the output from a human examiner could be used in a neural network, however this method did not work for practical cases [15] other than in the database. The study of De Kinder[16] is focused on using 3D laser triangulation for bullets, since similar correlation algorithms can be used.

Commercial systems exist on the market for automatic tool mark comparison [17] and IBIS[18] for bullets. The system for bullets will extract a signature of the striation mark and compare these. For bullets, the bullet it is recommended they are the same composition, since otherwise differences in the striation marks might result depending on differences in hardness of the material. One advantage with bullets compared to tool marks with screwdrivers is that the striation marks are more reproducible, since most often the bullet can only leave the firearm in one direction. With tool striation marks it is often not known which angle is needed to reproduce the mark.

For the speed of the algorithm for the correlation of striation marks it is most optimal to have a short signature with which to compare the database. The advantages of this method are that we can combine the surface of a striation mark to a one-dimensional string of gray values or depth information. In this way artifacts of the surface can be averaged. For the explanation of the algorithm we will continue in gray values, however instead of gray values, one can also read depth-values.

Our improved algorithm will follow the striation lines, and then sample a signature of gray values with the following approach:

The user selects an area of the tool mark that should be sampled manually. The reason for user interaction is that the user can determine which part belongs to the striation mark, and which part belongs to damages or other artifacts.

We assume that the striation lines are horizontally placed in the image, however it is nearly impossible to place them exactly horizontal. For this reason we will follow the striation lines (or depth information), and calculate the signature from this.

The area that is selected should contain the visible striation mark. Furthermore the user should validate the final signature that is calculated by the algorithm.

In our previous approach we would just average all gray values. If we have an image g(x,y) were g(x,y) is the gray value of the image at position x,y, we can average the gray values for N vertical lines, we have a signature :

$$\bar{g}(y) = \frac{\sum_{x=0}^{x=N} g(x,y)}{N} \tag{3}$$

However the problem with this approach is that all striation lines should be horizontal. To compensate for this, we have developed a method that will follow the striation lines themselves.

This method will work on a basis of 2x3 pixel matrix. We take the line g(x) out of the image and compare it to g(x,y) by three pixels. We average the gray values of g(x,y) with g(x,y+1). Furthermore we make a second line that is shifted g(x+1, y+1/2). This is conducted by averaging g(x,y+1) with g(x, y):

$$g(x, y + \tfrac{1}{2}) = \frac{g(x, y) + g(x, y+1)}{2} \qquad (4)$$

We also compare these gray values with each other, and calculate the same for g(x,y-1/2) and g(x,y-1).

In table 1 an example is given of comparing two lines.

Table 1: **Example of comparing two lines with the adaptive zoom algorithm. The shift of –1/2 will result in the best result for this case for a gray value of 150 in line 1.**

Line 1 g(x,y)	**Difference**	**Line 2 g(x+1,y)**	
50	75	75	G(x+1,y-1)
100	0	150	G(x+1,y-1/2)
150	-25	175	G(x+1,y)
200	-75	225	G(x+1,y+1/2)
250	-125	275	G(x+1,y+1)

Then we shift a pixel and do the same for g(x+1,y+1). If the difference between the pixels is better when shifting y-1/2, this

Figure 9: The result of sampling an area of a striation mark in a striation mark digitized with the OMECA.

will be done the second time that the values are approaching to each other. In this way this sampling method is repeated for all lines that were selected. Finally the average signature is displayed, and the user can validate to result. In Figure 9 an example is shown using this algorithm for a 3D-profile that is displayed in gray values. The user can check if the resulting signature is characteristic for the striation mark by checking the striation match.

A problem still remains for the 3D-case if there is a slope in the z-direction. In Figure 10 an example is shown of an image with a slope in the z direction. Since this slope is linear (it is caused by the fact that the cast is not completely flat on the surface), the user can select the edges of the tool mark in both direction and then we compensate for the tilt by assuming the slope is linear, and subtracting the relative differences of the four points with a linear algorithm.

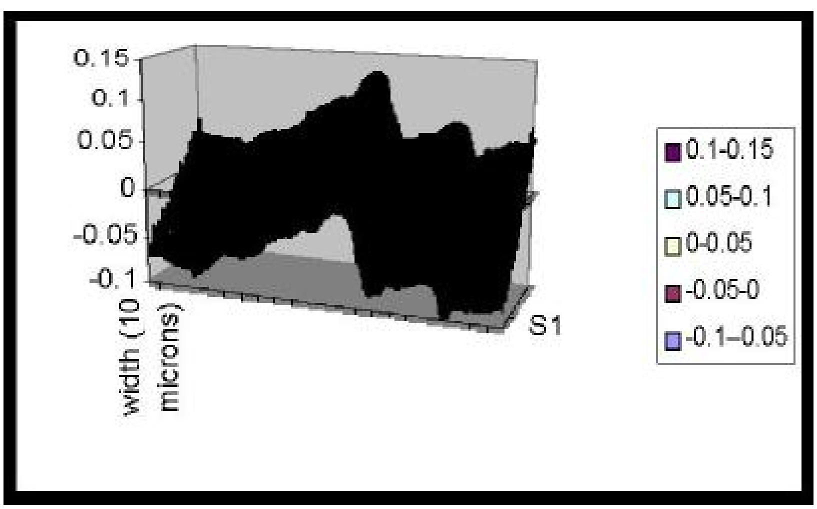

Figure 10: **3D-image of a tool mark with a slope in x and y-direction**

By calculating the standard deviation of the difference and shifting the tool marks relatively to each other in the memory of the computer, we can compare the complete database. The results will be a list of matches based with the marks with the lowest standard deviation of the difference at the top of the list.

4.8 Experiments

TESTSET

A small test has been prepared in which six screwdrivers are used. Of these six screwdrivers test marks were made with an angle of 45 degrees on wax. These striation marks were molded with gray silicon casting material. Then these marks were digitized with the structured light approach and with side light. It appeared that there are some artifacts and variations in the image due to: the largest number of stripes in the LCD projections, camera resolution and variations in the tool mark itself.

Since the current setup of our OMECA-structured light apparatus is limited to 6 mm, a part of the striation mark has been scanned. For each striation mark we have chosen to scan one edge with lines.

RESULTS

The results of correlation with the standard deviation of the difference are shown in Table 2 and Table 3. From this experiment it appeared that all tool marks that were compared to each other, were retrieved well. If we compare the results of the gray value images with the 3D-images, the algorithm will distinguish the striation marks with, on average, a 30 percent higher correlation factor (in our approach this is the standard deviation of the difference).

Table 2: **Correlation factors for gray value comparisons of the six screwdrivers**

	1	**2**	**3**	**4**	**5**	**6**
1	***17.3***	43.5	74.2	61.3	51.3	54.5
2	68.6	***27.7***	46.3	55.3	78.3	62.4
3	40.4	58.7	***15.4***	79.1	40.3	73.5
4	48.0	45.7	39.8	***20.2***	36.8	86.9
5	54.3	80.7	59.6	45.2	***23.2***	86.4
6	67.4	71.5	83.8	42.0	62.3	***20.6***

Table 3: Correlation factors for structured light comparison of the six screwdrivers

	1	**2**	**3**	**4**	**5**	**6**
1	***16.0***	47.7	81.2	114.4	44.4	107.0
2	55.8	***25.6***	71.8	113.7	82.1	110.8
3	81.3	47.4	***20.8***	66.8	47.3	104.5
4	101.8	103.4	56.4	***17.5***	70.2	70.2
5	91.2	90.4	100.0	89.3	***13.4***	97.5
6	92.8	88.3	113.7	83.0	97.3	***11.8***

4.9 Conclusions and discussion

Based on this research it appears that the use of three-dimensional information of a striation mark is useful compared to the two-dimensional side light image because we have a measurement of the depth information and are less sensitive to the influence of lighting of the surface.

In future research this method should be tested on larger databases of striation marks. Comparing striation marks with the current set-up of the OMECA equipment is not recommended because the area of scanning is limited to 6 mm. The equipment should be modified before continuing with large-scale experiments.

A different approach that might reduce the time of examination is digitizing the shape of the blade of the screwdriver, and then comparing the striation marks with the tool mark. In this case we would not have to make test marks anymore, and less time is needed for making the comparison with the database (if a proper way of digitizing the blade is used). Another area of research is the impression marks and comparing them with the 3D data of the tool itself.

In Figure 11 is shown that the shape of the blade of the screwdriver might also be used for distinguishing the tool mark easily. In this way a fast pre-selection is possible based on a small signature of the shape of the blade.

Figure 11 : Shape of the upper part of the blade of the screwdriver visualized in 3D-information

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5 Databases of Cartridge Cases

This chapter has been submitted to Forensic Science International. It is received 18 July 2000 and is accepted 27 October 2000.

Geradts, Z; Bijhold, J. Hermsen, R, Murtagh, F; Image matching algorithms for breech face marks and firing pins in a database of spent cartridge cases of firearms, Forensic Science International 2001, June 2001, Vol. 119, No. 1, pp. 97-106.

5.1 Introduction

In the Netherlands Forensic Institute (NFI) a research study has been carried out for automated comparison algorithms of cartridge cases. This study is a part of an evaluation of the different systems on the market for handling databases of cartridge cases and bullets.

The reason to compare the different methods of image matching is that the methods are proprietary. For use in a forensic laboratory it is important for quality assurance to understand why a certain image is not found in top matching ranks and to have more background on the image-matching engine. Another reason for this research is to improve the results of image matching.

5.1.1 Forensic Examination

When a firearm is loaded and fired the mechanisms and part in the firearm that come into contact with the cartridge case cause impressions and striations that can be characteristic for the firearm being used. The striation marks on bullets are caused by the irregularities in the firearm barrel.

The cartridge case ejected shows marks at the primer (Figure 12) that are caused by the firing pin and the breech face as the cartridge is repelled back in the breach by the force of rifling. The feeding, extraction and ejection mechanisms of the firearm will also leave characteristic marks.

In the Forensic Science Institute these marks on cartridge cases and bullets are compared with the test fired ones. Often the cartridge case is the most important forensic specimen in the identification of weapons, as bullets are commonly deformed by the impact. The examiner can also determine, using class characteristics what kind of firearm (often make and model) has been used.

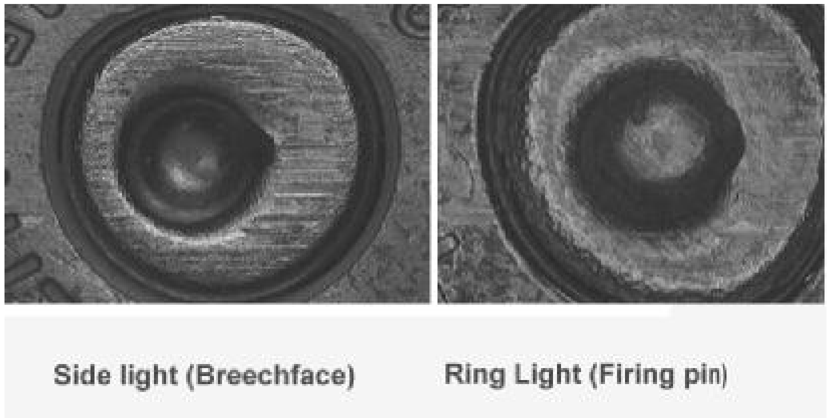

Figure 12 : Image of breech face with sidelight and image of firing pin with ring light

5.1.2 Ballistic Imaging Systems

DRUGFIRE [1] and IBIS[2,3,4,5] are databases that can be used for acquiring, storing and analyzing images of bullets and cartridge cases. These two systems have been evaluated at our laboratory.

Both systems capture video images of bullet striations and of the markings left on cartridge cases. These images are used to produce an electronic signature that is stored in a database. The system then compares this signature to that of another fired bullet or cartridge case - or to an entire database of fired bullets and cartridge cases. The user enters the cartridge case in the database for comparison, and can limit the search to using metadata (e.g. caliber, date limit). Then, the system produces a hit list that shows a ranking of all cartridge cases based on the similarity, as measured by the system, between the cartridge under investigation and the cartridges in the database. The system functions properly if all relevant matches are in the top of the hit list.

The methods of image matching applied in these systems are not known. However patents[2,3,4,5] applied by one company describe state-of-the-art image matching methods. The system of IBIS is now used most often, and since the images are acquired in a reproducible way by a special kind of lighting, the ring light, it is expected that this system give the best matching results.

Other systems that have been described on the market are the system Fireball[6], the French system CIBLE and the Russian system TAIS. These systems also use image-matching techniques.

Three-dimensional measurement of the striation marks by laser triangulation[7] or by fusing the images with different angles of coincidence are described in the literature[8].

Since the firearm examiner is used to comparing side light images and not three-dimensional images, development and acceptance of 3D-image matching methods progresses slowly. Therefore this study is focused on the matching of side light and ring light images.

5.2 Image matching

For this research we tested image-matching techniques, which are available from the literature[9]. There has been much interest in searching of image databases. Several commercial and research systems as QBIC, Virage and Photobook exist[10,11]. These systems search in the contents of images. They generally take features from images, and index these features as descriptors that are easily searchable. The results of searching these databases are generally influenced by the following differences between two matching images:

- Noise
- Rotation and shift
- Difference in light source

Further differences that are typical for databases of cartridge cases:

- Difference in cartridge case metal (material, type, brand)
- Wear of firearm
- Wear of cartridge case
- Marks between two shots can be different for statistical reasons in the shooting process; this means that sometimes parts of striation and impression marks are visible that are not visible with the next shot

In forensic investigations, the firearm examiner determines which marks on cartridge cases are similar. The approach of this research is a combination of shape of the firing pin and the texture of the impression marks. Since the light conditions and the image of the marks do change depending on the marks, methods have been implemented that compare the gray-scale images. In practice it turned out to be important to have an appropriate preprocessing image step to compensate for the variation of light. In the optimal situation the algorithm should only compare the marks caused by the firearm, and not any other features of the cartridge case, as damage and symbols.

In this research approaches are implemented that are both pixel based and feature based. The reason to use feature-based methods is to improve the calculating speed and to keep the selection restricted to marks.

5.3 Test database

For our evaluation of image matching algorithms we studied two kinds of images (Figure 12):

- Images of breech faces which are illuminated with side light
- Images of firing pins which are illuminated with ring light

We used a database of 4966 images, which were acquired by different firearm examiners from different institutes around the world using the Drugfire system under different circumstances (light sources and several views of the cartridge case). Table 1a shows the different calibers and the kind of images (side or ring light images). We tested the algorithms on all images (without prior knowledge).

The database consists of side light images of 49 different cartridge cases that have a known match. They are consistent in light conditions. These cartridge cases were fired from 18 different firearms of caliber's 9 mm Parabellum (15), .45 automatic (2) and .32 (1). Depending on the case, there are 2-5 similar marks on the cartridge cases. Some of these cartridge cases are from different test shots. The marks of the cartridge cases and the shapes of the firing pin are visually similar between the matches. These cartridge cases can be mixed with the rest of the database for the experiments with large databases. Five cartridge cases have a rotation of more than 10 degrees to each other. The 49 cartridge cases are also available as ring light images of the firing pin. There are marks in all ring light images of the firing pin that can be distinguished from each other visually.

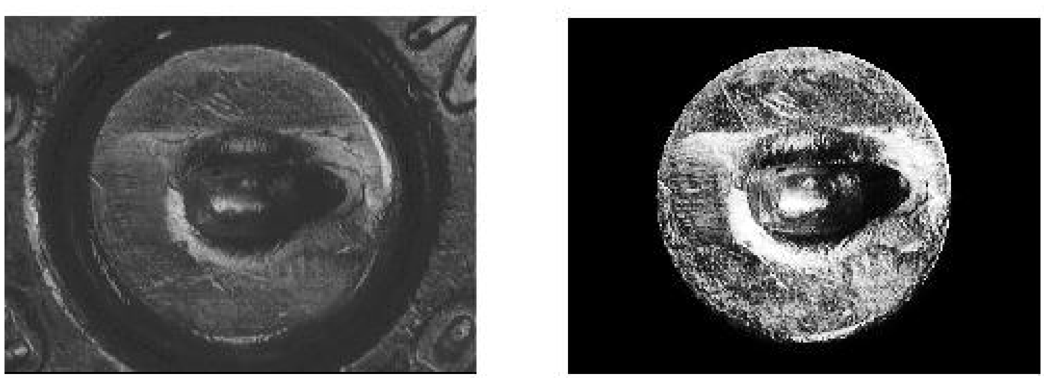

Figure 13: Preprocessing operation (left: original image, right: processed image)

5.4 Pre-processing

5.4.1 Equalization and masking

We first equalize the images, since the conditions of lighting differed for the cartridge cases in the database. On all images histogram equalization is used in an effort to compensate for differences in lighting conditions.

Since we would like to compare just the inner circle of the image (were most impression marks are), we select the circle manually and all pixels outside of this circle will get a zero gray value (Figure 13). This pre-processing has been carried out to all images that are in our databases.

Because a circular shape is compared, the image can be converted to polar coordinates. The polar image is calculated from the center of the firing pin, and in this way a polar image can be calculated. Since polar coordinates are used, the firing pin will cover a larger area in this image then with regular images (Figure 3). For our computation we have selected a 360x360 (angle x radius) image. The polar images are more appropriate for calculation, as the outside of the circle does not have to be modified. The polar images can be selected optionally instead of the regular images.

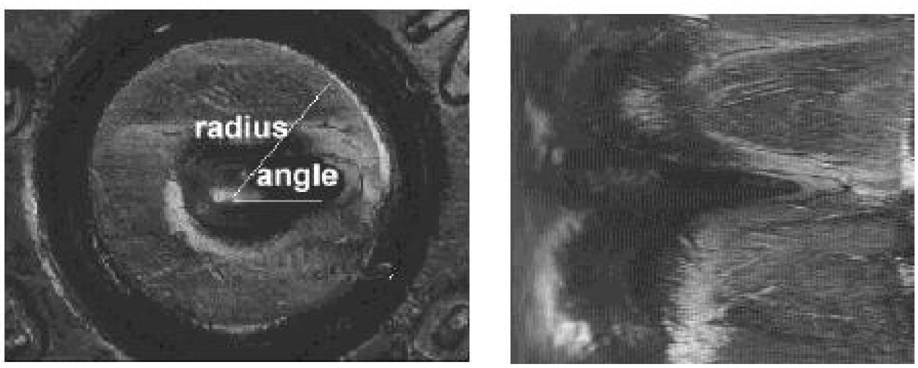

Figure 14 : Polar coordinate image of cartridge case (r,Ö)

Wavelets

There are a huge number of articles[12] on pattern recognition based on wavelet transforms. A wavelet transform is a localized function of mean zero. Often wavelets incorporate a pyramidal visualization. Wavelet functions are often wave-like but clipped to a finite domain.

Wavelet transforms are computationally efficient and they allow exact reconstruction of the original data. The reason for choosing a wavelet transform is that we can filter out the information of marks. Since wavelets can work as good filters for different details (from coarse to fine) in the image, the challenge is to choose a wavelet scale and type that is optimal for our marks (fine striation and impression marks).

We have chosen a wavelet transform that works on discrete data that is known as à trous (with holes) algorithm[13]. In this wavelet function the data is sampled by means of a smoothing function, the B3 spline. The different scales of à trous that are calculated can be added to each other and the result will be the original image.

The scale 1 of the à trous algorithm will give the finest details and the noise in the image. The higher scales will give the course variation of lighting in the image. In Figure 15 an example is given of four scales for a cartridge case computed with the à trous algorithm. In the third scale most information of the mark is given

5.5 *Image matching Methods*

In this section an overview is given of different image matching methods that worked for this database.

5.5.1 *Difference of two images*

For a computationally simple kind of comparison we take the variance of the difference in gray values between two images (which is also used in previous research[14]).

The hit list is created by sorting the variance from small values for the best matching to high values for images that do not match that well.

Given that the user of the database has to position the cartridge cases with the standard procedure, it might even be positioned 180 degrees rotated. This is caused when the examiner finds the wrong position of the cartridge case in the firearm based on the marks. Also small rotation angles are allowed. We tested the results by rotation of the cartridge case. It appeared that our results are invariant for rotation of up to 5 degrees. The average standard deviation is low and the image that we tested will be retrieved in this situation. The images that are digitized in our laboratory are digitized by using the protocol, however with the other images, it is not completely sure if the protocol is exactly followed, since they are acquired in many different places in the world.

We subtracted a given image from each image in the database and compared the standard deviation of the result. It appeared that 21 out of the 49 images were in the top positions. 15 were in the top 5 percent of the database. This means that the examiner should browse through 250 cartridge cases before knowing there is no match. This does not work well in practice, since it is a time consuming work. Five cartridge cases were in the top 50 percent of the database. These five cartridge cases had a rotation of more than 10 degrees, and this caused the difference. For this reason this approach is not effective.

It appeared that the influence of the shadows and marks in the firing pin could disturb the results of image matching. One of the reasons is that the firing pin mark is a deep mark, and that the shadows and the visual marks in the

Figure 15: **Four scales computed with the à trous wavelet transform**

firing pin is of influence on the final matching result. There is an alternative, namely to filter the firing pin mark out of the image, however the shape of the firing pin is also important for class characteristics. The shape is just a fast way of pre-selection. For the brute force way of comparison it appeared that if we reduce the influence of the correlation of the primer area with fifty percent that the final correlation results improved. We have tested different percentages for these 49, and an optimum was found around fifty percent. If both ring light images exist and side light images, the influence of the firing pin can also be reduced to 0 percent, since the ring light image will show a good image of the shape of the firing pin. The correlation results of the ring light images and of the side light images should be combined.

Compensating for rotation and translation

From examination of the images, it appeared that some of these images were slightly rotated and translated. For this reason we tried to compensate this influence by rotating and translating the images themselves in the memory of the computer, and calculating the minimum of the standard deviation of the difference in gray values. With those compensations, it appeared that all images were found in the top positions. This approach worked both in the polar coordinates as well as in the raw images. The computation is done by rotating 360 degrees in steps of one degree and shifting 40 pixels in x and y-direction in steps of one pixel. The computation took more than one month on a Pentium-II PC for 49 images; for this reason this method has not been tested with the complete database.

5.5.2 ***Log Polar***

A classical technique for registering two images with translation misalignment involved calculating the 2D cross-image matching function[15]. Image registration algorithms are important for this kind of research, since the position of the marks is not known exactly.

The maximum of this function yields the translation necessary to bring the images into alignment. This function has the disadvantage of being sensitive to rotation and scale change. Even small rotations of a few degrees can reduce the peak of the cross image matching function to the noise level.

By using the invariant image descriptors in place of the original images, it is possible to avoid this problem. One such descriptor is the log-polar transform of the Fourier magnitude, which removes the effect of rotation, and uniform scaling into shifts in orthogonal directions[16].

Results

We tested the log polar transform on raw images. It appeared that 5 out of the 49 cartridge cases were in the top position. All images were however in the first 6 percent (top 300) of the complete database. For this reason the method can be used as a faster selection method. The log polar transform took 7 days to calculate for the complete database of 4190 images.

Better results were found when using the third scale of the à trous transform on these images. All matching images were in the top positions. This method produced similar results as the brute force calculation.

5.5.3 Selecting features by tracking (KLT – method)

There are extensive studies of image matching for tracking[17]. Since tracking has many similarities with searching in a database of images[18], we have tested these algorithms. Often these algorithms are optimized for their speed. The features that are of interest are followed. Determining if a feature is of interest can be used for ranking it in a hit list. Tracking also has the problem of registration, since the camera might move, with image intensities that change in a complex way.

One of the methods that appears to work for a wide range of tracking problems, and that works fast, is the Kanade Lucas Tomasi (KLT) equation[19]. Good features (in this approach this means prominent features, as strong edges) are located by examining the minimum eigenvalue of each 2 by 2-gradient matrix. The features are tracked using a Newton-Raphson method of minimizing the difference between the two windows. Multiresolution tracking allows for even large displacements between images.

Based on this equation, the details in the images that are prominent are selected as points. From each image these points are calculated once and stored in the database. Then the position of those points is compared as a signature. The number of points that are matched between two cartridge cases is a measure of similarity between the two images.

Results

We can work with this method using the equalized images. Due to noise and variation in the images, the features are not reproducible that well. For this reason, we have combined this with the different scales of images. In each image 100 features are selected and compared to the other images.

It appeared that some images were low in the hit list, because of variations in the light conditions for the raw images, and at scales 1 and 2 it appeared that there were misses. This means that no image matching points were found. The scale 3 appeared to work fine for these marks both for ring light and sidelight.

5.6 Conclusions and Discussion

We tested different image matching algorithms for marks on cartridge cases, using 49 cartridge cases from 18 different firearms. For each match several firearm examiners determined that they were shot with the same firearm.

In cases where the positioning, and the light conditions among the marks in the cartridge cases was reproducible, a simple computation of the standard deviation of the subtracted gray levels put the matching images on top of the hit list. For images that were rotated and shifted, we have built a "brute force" way of image translation and rotation, and the minimum of the standard deviation of the difference is computed. For images that did not have the same light conditions and were rotated relative to each other, it was useful to use the third scale of the "à trous"-Multiresolution computation.

From our experiments we conclude that the most optimal method for comparison is possible by a combination of correlation methods. The preprocessed images with the third scale à trous wavelet in combination with the log polar transform worked best. To improve the speed of image matching the KLT-method could be used first for the top five percent for a faster pre-selection. After this log polar correlation can be used, and then it is possible to have a result in a few minutes. Furthermore based on the results of the log polar correlation, a brute force method can be used for the top matching images. The images and image matching methods that are used have marks that can be distinguished visually.

For further improvement, it might be useful to have the refinement in which the user selects the areas that are relevant on the cartridge case for their marks. Sometimes the firearm examiner can have more information that some marks on the cartridge cases are due to damage not caused by the firearm. Examples of this damage are text imprints in the firing pin.

The use of optical processors[20, 21] or parallel processors implemented in hardware is an option to improve the speed of the image matching compared to our brute force method.

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6 Database of Shoeprints

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Geradts, Z; Keijzer, J ; The Image database REBEZO for Shoeprints with developments on automatic classification of shoe outsole designs, FORENSIC SCIENCE INTERNATIONAL, (15 SEP 1996) Vol. 82, No. 1, pp. 21-31

6.1 Introduction

In the Netherlands there are many crimes each year in which shoeprints are found. Since the collections of shoes from suspects and shoeprints found at the scene of crime, are very large it takes a lot of time to compare them. In 1993 in the Netherlands approximately 14.000 shoeprints were found at the scene of crime. There were in the Netherlands in 1993 approximately 500 identifications on shoeprints.

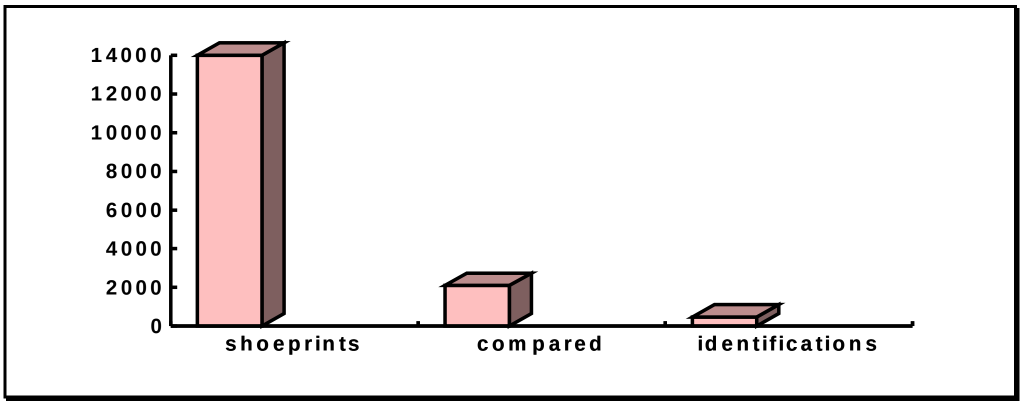

Figure 16 : Number of crimes solved with shoeprints in 1993

For this reason it might be useful to enter images of shoe-profiles and shoeprints in the computer. In our laboratory the software REBEZO is developed.

The database REBEZO consists of three parts :

- a collection of outsole designs of shoes which can be bought in shops
- a collection of images of shoe outsole designs from suspects
- a collection of footwear impressions found at the scene of crime

From the collection of outsole designs it can be determined from what brand and model of a shoe might have caused a shoeprint. This can be useful for investigations. The shoe outsole designs from the shoes of suspects are stored to make connections between these shoes and possible future crimes. Further the footwear impressions found at the scene of crime are stored to compare them with the shoes of the suspect. The system is used for pre-selection of shoeprints and shoe-profiles and not for the actual comparison.

6.2 Classification scheme

The shoes and shoeprints can be added to the computer system with a video camera. The user fills in the input screen. For reproducible results, standards are developed for the magnification and in which direction the shoeprint or shoe should be stored.

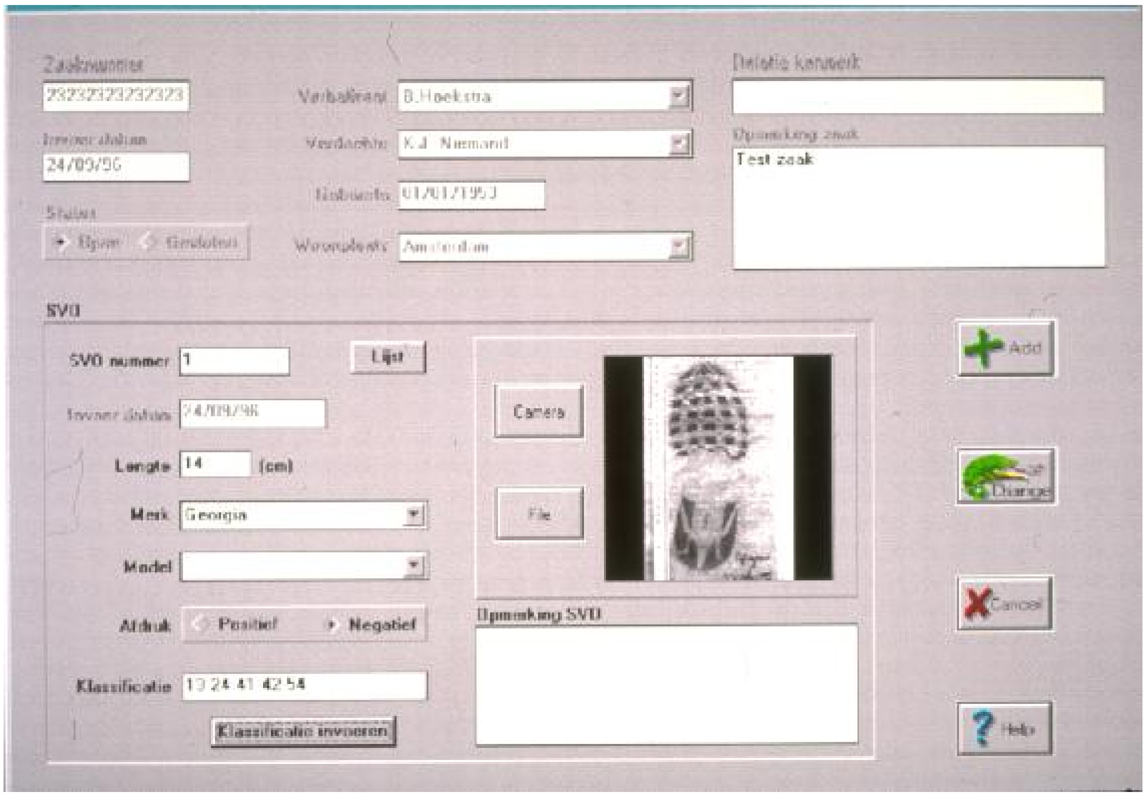

Figure 17: Screen for adding the shoeprint to the system

For retrieving the images it is very important to fill in the classification screen. This screen gives a classification scheme that has been developed in the Netherlands with the Dutch police. In many countries there are developments of shoe profile systems and the classification systems[1 2 3 4] 5].

The codes shown in Figure 18are used for our classification. A more detailed description of the codes is available. The computer program shows an example image when clicking on the different codes. It appears that the user classifies more consistently with sample images.

- 10. structure
  - 11. crepe
  - 12. plain
  - 13. profile

If profiled than a sub classification exists :

- 20. lines
  - 21. horizontal
  - 22. vertical
  - 23. slope
  - 24. vertical
  - 25. waving line
  - 26. zigzag
  - 27. edgy line
  - 28. irregular line
- 30. triangles
  - 31. symmetric
  - 32. not symmetric
  - 33. irregular
- 40. squares/rectangles
  - 41. squares
  - 42. rectangles
  - 43. parallelogram
  - 44. not regular
- 50. surfaces with more than four angles
  - 51. five angle
  - 52. six angles
  - 53. more than six angles
  - 54. irregular
- 60. rounds
  - 61. dots
  - 62. circles
  - 63. spin round with one ring
  - 64. spin round with more than one ring
  - 65. ovals
  - 66. parts of rounds
  - 67. irregular
  - 70. figure
  - 71. logo
  - 72. picture
- 80. terms
  - 81. brand name
  - 82. type
  - 83. size
  - 84. others

Figure 18: classification codes

Comparison screen

The user can compare the shoeprints with each other, the shoes of suspects and the shoes of the reference database. Figure 19 shows a screen with on the left the live image of a shoeprint and on the right test print of a shoe. In REBEZO all three databases can be compared to each other.

The user can mirror and rotate the images. This is convenient for the comparison of inverted images.

Figure 19 : Comparison Screen

Reference collection

The reference collection will be build by making test impressions with a foam box. Then those foam boxes will be photographed and the photographs are stored on Photo-CD. The images are compressed further in REBEZO in such a way that 3000 images fit on a CD-ROM.

6.3 Automatic Classification

Since there are many differences between users in classification codes that are assigned to the shoes, a research project is started for the automatic classification of shoe profiles. The aim of the project is to make suggestions for the users for the codes and the final aim will be an automatic pre selection system. For this project the image-processing package Khoros[6] has been used.

First the shapes are segmented with a labeling process. The shapes are segmented with some morphological filters and then the labels are given to the separate shoe profiles. A sample of the labeling process is shown in Figure 20.

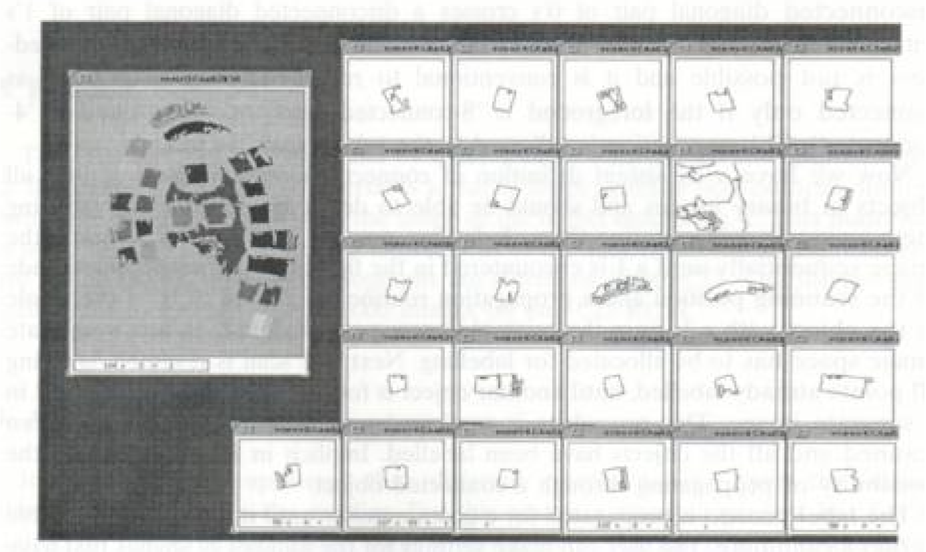

Figure 20 : Labeling and segmenting of images from shoeprints

For the classification the next methods are evaluated:

- distance minimization method
- overlap/best fit
- invariant moments
- erode/dilate
- ellipse method
- contour analysis-methods
- localized receptive field classification
- two-dimensional shape analysis with FFT

From our research the invariant moment method appears to work well in combination with the two-dimensional analysis with FFT.

Invariant moments

The recognition of the different patterns should be independent from the size, position and orientation in our classification.

The two-dimensional (p+q) order of the density-distribution function ρ(x,y) is defined as :

$$m_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^p y^q r(x,y)dxdy;$$
$$p,q = 0,1,2,.....$$

Equation 5

The central moments μ(p,q) are given by :

$$m_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} (x-\bar{x})^p (y-\bar{y})^q \; r(x,y)d(x-\bar{x})d(y-\bar{y});$$
$$p,q = 0,1,2,.....$$

Equation 6

In which :

$$\bar{x} = \frac{m_{10}}{m_{00}}; \bar{y} = \frac{m_{10}}{m_{00}}$$

Equation 7

The second and third order moments are calculated by Ming-Kuei Hu which are invariant for size, position and orientation.

For the shoe profiles we have determined different invariant moments. With the invariant an ideal shoe profile was classified. The results are shown in Table 4. It appears that it might be difficult to differentiate the square and rectangle from each other. Further noise in the image will result in loss of detail.

Invariant moments	**M1**	**M2**	**M3**
square	0.1665	0	0
rectangle (1 x 1.05)	0.1667788	4.275	0
rectangle (1 x 10)	0.8145	6.80625	0
line	>0.8415	>0.680625	0
triangle (symmetric)	0.1924656	0	4.565308e-3
triangle (asymmetric)	0.1595188	0	0
quarter of a circle	1.77873e-1	2.845261e-3	8.84429e-4
half of a circle	0.2040900	1.335299e-2	1.190370e-3
Circle	0.1591552	0	0

Table 4 : invariant moments of ideal shapes of shoe profiles

6.4 Classification process

The labeled shoe profiles are analyzed further with Fourier Features. Since more data reduction is required for using this information in a neural network, a nearest neighbor calculation is made. The features that are left are entered in a neural network.

For this research we used software that was available from the University of Lisbon[7][14]. The centre point of the figure is determined. From this point the distance to the edge of the figure is determined. From the polar diagram the Fourier Transform is computed. This method is not sensible for translations and scales, since the distance is relative. A rotation in the figure will result in a phase shift in the Fourier transform. The Fourier-features (like frequency and amplitude) are computed resulting in 126 features.

The problem is now selecting the right features for the neural network. Since the supervision of machines is a generic problem, the feature selection algorithm should of general-purpose nature. From the initial dimension of feature vectors only a small amount will be used for selection.

With the reduced feature set a classifier is designed. This classifier might be a neural network, a Bayesian model or a non-parametric model. To analyze how well the chosen feature set will perform the classification error estimation is determined. For these analyses we use the Sammon[8] mapping, since more than 3 dimensions are not easy to visualize.

First we tried the images from the foam boxes. Since this is a 3-dimensional impression some problems result with the labeling and recognition. For this reason we made black shoeprints and scanned them with a video camera and frame grabber. In these shoeprints the different shapes can be labeled and the different shapes are tested.

In Figure 21 the Sammon-plot is shown with the two best Fourier features. In this Sammon map it appears that not every shape can be distinguished with two features. So more features are required for this method. In Figure 22 is shown that many different shapes can be distinguished from each other. The problem is however that vertical and horizontal lines cannot be easy distinguished.

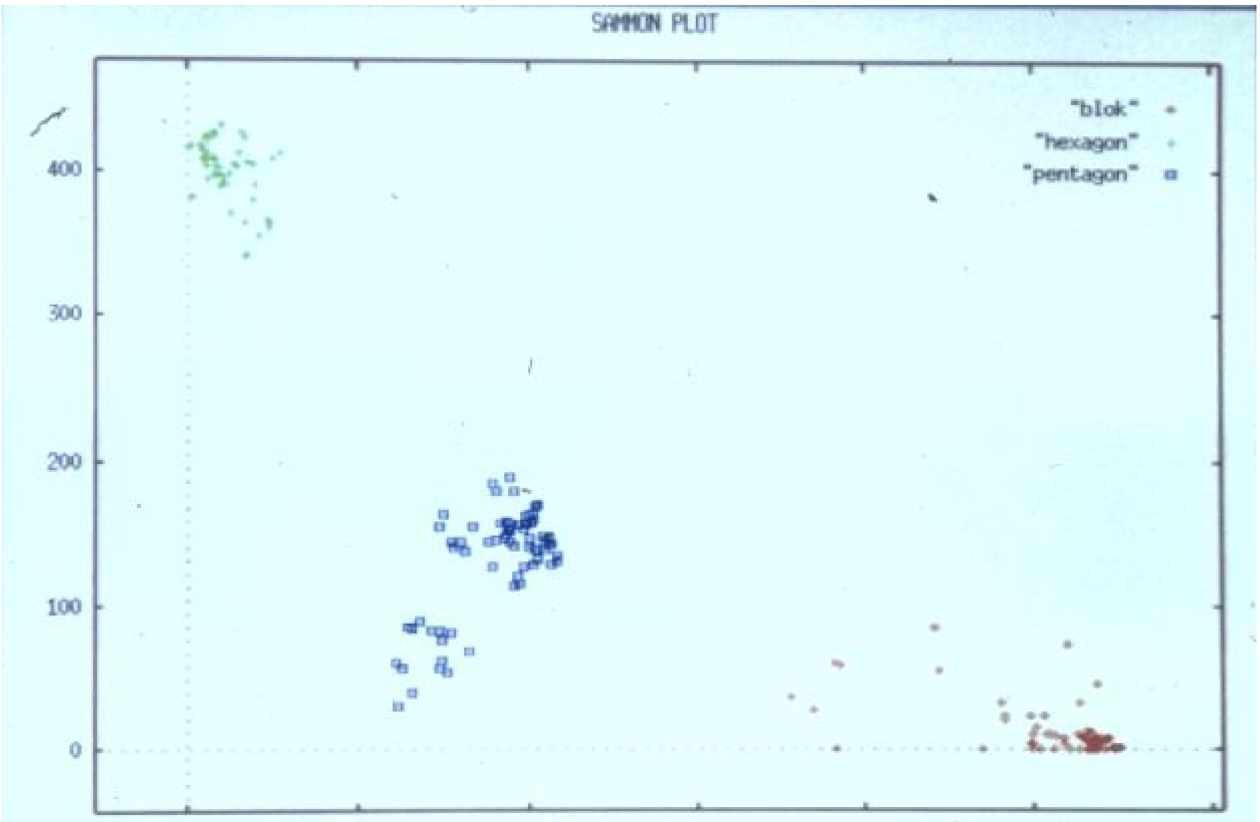

Figure 21 : Sammon-plot of the two best Fourier features

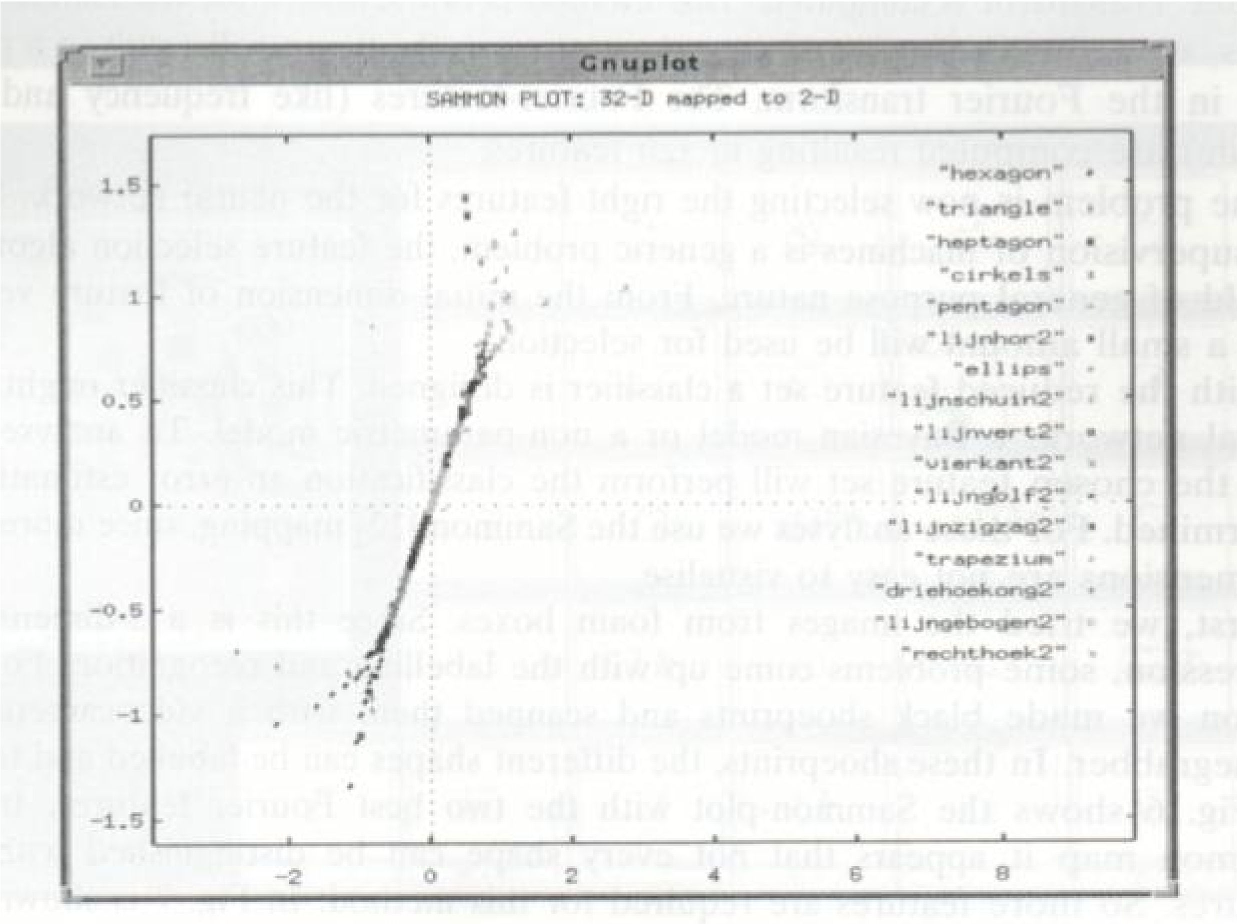

Figure 22 : Sammon-plot of the 32 best Fourier features

A single-hidden-layer feed forward network trained with back propagation[9] is used as the recognition network. Experimental results have shown[10] that this type of network can classify with high accuracy noiseless as well as noisy images. Therefore we chose a single-hidden-layer network as pattern's classifier. The program used is SNNS from the University of Stuttgart. The network can classify the different patterns. The problem with horizontal and vertical lines is not yet solved, however.

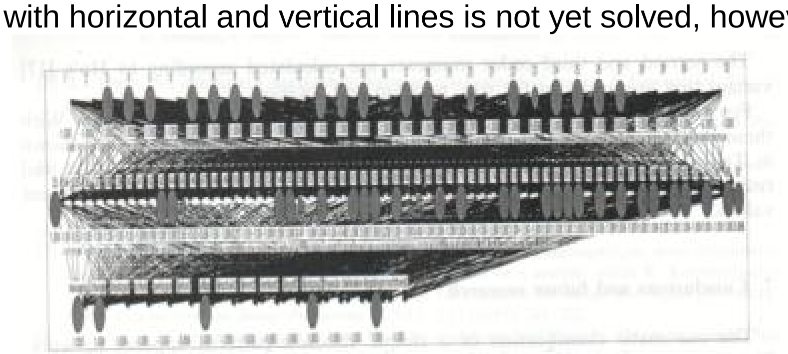

Figure 23 : neural network used for the classification

6.5 Conclusions and future research

The automatic classification of good shoe sole-patterns appears to work. Adding an entry in the network with the rotation variant moment can solve the problem with the rotation of the pattern. In future research the combination of moment information and Fourier features will be used for the neural network.

Pattern recognition of the shoe-sole-patterns in a foam box might be difficult, since these have three-dimensional information. Making two images illuminated from both sides of the foam box might solve this problem. Other solutions might be a 3D-acquisition of the image.

The shoeprints that are found at the scene of crime often do not have a good quality. So they will be difficult to classify automatically. Since the shoes from suspects and shoes from the shops are available, good quality test prints can be made.

The best approach for the comparison might be to classify the shoeprint by the user and selecting the different shoe-profiles on the screen. The classification can be modified, since not so many codes have to be used when the relative position of the profiles is taken into account.

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7 Databases of logo’s of Drugs pills

This chapter has been submitted to Journal of Electronic Imaging in February 2001.

Geradts, Z; Bijhold, J; Poortman, A, Hardy, H; Databases of logo’s of Drugs Pills – submitted to Journal of Electronic Imaging

7.1 Introduction

At the drugs department of the NFI a large number of illicitly produced tablets, mostly containing MDMA and amphetamine, are submitted for forensic analysis. Information on the chemical composition and the physical characteristics (i.e., diameter, shape, height and weight) and images of the clandestine tablets is available in a database. The illicit manufacturers often make use of punches resulting in tablets that bear an imprint consisting of all sorts of registered trademarks and fantasy figures. In this research a study has been made for different ways of contents based image retrieval of the logos. In an example of a logo on a drug tablet is shown.

7.2 Contents Based Image Retrieval (CBIR)

The correlation method for retrieving the images in this database should be easy to use and invariant to rotation, translation and light conditions. The images of the tablets are acquired with a standard camera with a side light source. This approach may result in differences in the images of the logos due to light variations. Another factor that has to be considered is that a tablet itself can be damaged, and the logo is not completely visible anymore. Since the three-dimensional logo is captured with a regular camera, the resulting 2D shadow image has to be compared. The correlation method should be insensitive to these factors.

Many research groups[1] are working on image retrieval based on contents. Current research is accessing visual materials by use of multimedia in education, entertainment and publishing companies. Other large-scale image databases include newswire collections and collections such as patent and trademark image databases containing over 600,000 images.

These and other large-scale image databases require new techniques and applications for retrieval and have caused new initiatives for improving access to collections of visual materials. The research is focusing on several broad areas: image indexing and classification, image users and image uses and machine methods for image parsing.

Figure 24: Example of a logo on a drug tablet

A concern with image indexing and classification is the appropriateness of text-based methods for materials other than text. Another concern is that we need to index and retrieve the images quickly. For our drug tablets the logos often are signs for brand names or other fantasy figures. At our Institute a text string of what the examiner recognizes in the logo is entered as text in the database. The difficulty with this approach is that different examiners will classify a logo with a different text string. It is well known that this problem exists from literature.[2] Since some logos are similar to text, OCR-methods[3] can also work for these databases. However, in the OCR-case there is a 2-Dimensional image, and we have to deal with shadow images of a 3-Dimensional shape.

In Contents Based Image Retrieval in general, several layers can be distinguished. An overview article can be found on the Internet at http://www.jtap.ac.uk/reports/htm/jtap-039.html.

The current Level 1 CBIR-techniques is query by example. This means for our case that a drug tablet is entered in the system and it has to be compared with the complete database.

A technique that is often implemented is the use of color histograms in images. This method is not relevant in this approach, since the same stamp can be used to manufacture tablets with different colors. Texture is another basic visual feature used in contents-based retrieval systems. Texture similarity can be useful when distinguishing areas with similar color. A variety of techniques have been used which takes into account the contrast, coarseness, directionality and the randomness.[4,5] However, for our drug tablets we would like to compare logos and often these do not contain texture.

We would like to retrieve the logos by shape. Two main types of shape features are commonly used:

- Global features (aspect ratio, circularity and moment invariants)[6]

- Local features (consecutive boundary segments)[7]

Other methods for shape matching include elastic deformation of templates,[8] and comparison of directional histograms of edges extracted from the image.[9]

In our case we have a drug tablet with a three dimensional logo where only the 2D-view is available. If there would be a standardized way of digitizing the tablet each time in the same way, this would not be a problem, since the 2D-view is reproducible. This might be the case with known logos where the examiner knows how to position the drug tablet. However, there are also other figures that are not known, and these will be positioned randomly. For dealing with 3D-images that are acquired with a 2D-image, there is research available of plausible 3D-models from the 2D image.[10]

There is also research by other types of primitive features. This is position in the image or complex transformations of images as with wavelets or fractals.

The Level 2 system of CBIR will classify the image automatically and then search based on the text string (e.g. OCR). Level 3 systems will recognize on more subjective grounds; however, research in this area is rare. These methods are not evaluated in this research.

7.3 Implementations

To demonstrate the feasibility of new techniques, many experimental systems have been developed by research institutes and by commercial manufacturers.

7.3.1 Commercial Systems

The most well known commercial database is QBIC of IBM. The system extracts and stores color, shape and texture features from each image in a database, and uses R^*-tree indexes to improve the search speed.[11] This database is available on the web. When searching for an image, the system matches the features from the query and stored image and displays similar images on the screen as thumbnails. An evaluation copy is available from the web at http://wwwqic.almaden.ibm.com. Virage[12] [13] and Excalibur[14] are other well-known commercial systems.

The system Imatch is a system at the low-end part of the market that can be downloaded from the Internet at http://www.mwlabs.de/, and there is an evaluation version available for download. A disadvantage for evaluation of these commercial systems is that there is no source code available and the algorithms that are implemented are often not described in literature or patents.

7.4 Developments by Research Institutes

Initiatives that have the source code available on the web include Photobook[8] (http://www-white.media.mit.edu/vismod/demos/photobook). This system is also known for its face comparison features.

The University of Singapore had a research project[15] for CBIR on trademarks where Fourier Descriptors and Moment Invariants measure features of logos. Since the logos in our database often contain trademarks, this research is similar to our approach.

In the past we have tested the Fourier Descriptors and Moment Invariants with neural networks for the shape of profiles in shoeprints.[16] However, in the meantime many other methods have become available.

Currently, we are working on a project together with the University of Amsterdam for implementing the database in PicToSeek.[17] This project is also related to trademark retrieval.

7.4.1 MPEG-7

MPEG-implementations are a standard for video and audio compression, and they are used in a wide variety of equipment and on the Internet. Where MPEG-1, MPEG-2 and MPEG-4 focused on coding[18] and compression, MPEG-7[19] is emerging as a new standard for searching in video and audio streams. The source codes of the algorithms and the test environment are available. The MPEG-7[20] does not define a monolithic system for content description but a set of methods and tools for the different steps of multimedia description. It will standardize: the set of descriptors, the set of description schemes, a language to describe description schemes and one or more methods to encode descriptions. MPEG-7 is developed for Audio and Video. It contains all descriptors as color, shape texture and others. In the current standard three shape descriptors are applied: object bounding box, region-based shape and contour-based shape. It is known that MPEG-7 is a framework that develops rapidly, so many other methods can be implemented in this framework in the future.

7.4.1.1 *Object bounding box*

The object bounding box descriptor addresses the coarse shape description of visual objects. A bounding box of a visual object is the tightest rectangular box that fully encompasses that visual object such that the faces/sides of the box are parallel to the principal axis of that object. The descriptor can describe bounding boxes for 2D and 3D objects.

The descriptor consists of three parts. The first part describes the size of the bounding box itself. This portion is rotation and shift invariant. The size is described in normalized coordinates, such that the description is resolution independent.

The second part is the density of valid samples in an object's bounding box and serves as a confidence measure for this descriptor. It can be used to compute the area of a 2D object or the volume of a 3D object.

The third part is optional and describes the spatial position of the visual object in 3D coordinate axes and its orientation.

The extraction of objects consists of three parts:

- Segmentation (just a simple kind of segmentation with labeling pixels)
- Extraction of the bitmap of the object of interest
- Estimating the bounding box

The process of estimating the bounding box is broken down:

- Estimating the orientation of the object (computing Eigen vectors of the tensor of inertia of the object. The object is in a binary format.)
- Normalizing the units

The matching process in general works as follows:

- Compute the descriptors of all images in the database and of the image that is queried for
- Compute the distance between the different descriptors for each image
- Sort the distance in ascending order
- Present the top results in the sorting to the user

7.4.1.2 Region-based Shape

The region-based shape of a subject will consider the lack of perfect segmentation processes. The region-based descriptor cannot only describe diverse shapes efficiently in a single descriptor and it is robust to minor deformation along the boundary of an object. This method is used for trademark retrieval.

The process consists of:

- Extraction of vertices (segmentation, extraction of the bitmap of object of interest, estimation of a closed contour and encoding of the polygon vertices)
- Determination if a given point is inside or outside the figure represented by the vertices

7.4.1.3 Contour based Shape

Contour-based shape descriptors capture characteristic shape features of an object or region based on its contour. It uses the Curvature Scale-Space representation, which captures perceptually meaningful features of the shape.

The representation in Curvature Scale-Space has the following properties:

- It captures the characteristic features of shape
- It reflects properties of the human visual system
- It is robust to partial occlusion of the shape
- It is robust to perspective transformations
- It is compact

The process of CSS detection is as described by Mokhtarian.[21] The representation of the contour shape is very compact, below 15 bytes in size. The object itself describes a closed contour of a 2D object or region in the image.

The descriptor itself is composed out of:

- The number of peaks in the image
- The highest peak height
- $$circularity = \frac{perimeter^2}{area} \quad \textbf{(1)}$$

- **(2)**

Where

And (x, y) is each point inside the contour shape and (x_c,y_c) is the center of mass of the shape.

- Prototype contour curvature vector. This element specifies the eccentricity and circularity of the prototype contour. The prototype contour is defined as the curve smoothed by means of filtering until it becomes convex. The convex contour is obtained by smoothing with the filter parameters corresponding to the highest peak.
- Xpeak, ypeak: parameters of the remaining peaks with reference to the highest peak. They are ordered in decreasing order. Xpeak [i] is the arc-length position and ypeak [i] is the height of the I-th peak. For example, of ypeak [2] = 0.5 this means ypeak [2] = 0.5*ypeak [1].

7.4.2 Log Polar

In our research for correlation of impression marks on cartridge cases,[22] we have used log polar correlation.[23] This method is rotation, translation and scaling invariant. The method is used for registering different images; however, it can also be used for searching in databases. The factor that is computed for the registration is a measure if the two images match. This method is more time consuming than the methods that have been previously described in this chapter.

By using the invariant image descriptors in place of the original images, it is possible to avoid the problem that correlation results disappear in noise level. One such descriptor is the log-polar transform of the Fourier magnitude, which removes the effect of translation and uniform scaling into depended shifts in orthogonal directions.[24]

In order to demonstrate the properties of this triple invariant image descriptor, consider the comparison between two images f(x,y) and g(x,y), which are related by a four-parameter geometric transformation:

g(x,y) = f(α(x cos β + y sin β) - Δx, α(-x sinβ + y cosβ) - Δy
(3)

The magnitudes of the Fourier transform are invariant to translation, but retain the effect of scaling and rotation:

$$G'(u,v)| = \frac{1}{a^2}\left|F\left(\frac{u\cos b + v\sin b}{a}, \frac{-u\sin b + v\cos b}{a}\right)\right| \qquad \textbf{(4)}$$

Where G (u, v) and F (u, v) are the Fourier Transforms of g (x, y) and f (x, y) respectively.

Mapping of the Fourier magnitudes into polar coordinates (r,θ) achieves the decoupling of the rotation and scale factors; rotation maps to a cyclic shift on the θ-axis, and scaling maps to a scaling of the r-axis:

$$|F'(r,q)| = \frac{1}{a^2}\left|F\left(\frac{r}{a}, q + b\right)\right| \qquad \textbf{(5)}$$

:

Where

$$r = \sqrt{u^2 + v^2} and q = \tan^{-1} v/u$$

A logarithmic transformation of the r-axis further transforms scaling into a shift:

$$|F'(r,q)| = \frac{1}{a^2}|F(r - \ln(a), q + b)| \qquad \textbf{(6)}$$

Where ρ=ln(r). The polar mapping followed by the logarithmic transformation of the r-axis is called the log-polar transform.

The optimal rotation angle and scale factor can be determined by calculating the cross-correlation function of the log-polar transformed Fourier magnitudes of the two images. It is important to note that the cross-correlation needs to be circular along the θ-axis, and linear along the ρ-axis:

$$XC(R,T) = \sum_{r=r_{\min}}^{r_{\max}} \sum_{q=0}^{2p} F(r+R, q+T)F'(r,q) \qquad \textbf{(7)}$$

Where F (ρ,θ) is equal to F (F (ρ,θ modulo 2π) and XC(R, T) is the two-dimensional cross-correlation function, with parameters R (difference in logarithm of scale factors) and T (difference in rotation angles).

The θ-axis-circular and ρ-axis-linear cross-correlation can be readily achieved by zero-padding only the ρ-axis direction and performing a circular cross-correlation with an FFT-based algorithm.

If the valid range of rotations is not known a-priori, then an additional cross-correlation may be necessary to remove the 180 degrees ambiguity in the rotation angle, because the Fourier magnitude of a real-valued image is an even function.

The correlation factor XC(R, T) is a measure for correlation between the different images. It is important with respect to the implementation of the triple invariant image descriptor algorithm the choice of the number of samples in the log-polar-domain. This number is based on a realistic memory requirement and a realistic representation in the log-polar-domain.

One way to approach the spatially variant resolution of the log-polar domain is to have the worst-case resolution equal to the log-polar domain equal the resolution in the rectangular domain. The log-polar domain resolution elements are:

$$\Delta q = \frac{\Delta l}{r}; \Delta r = \frac{\Delta r}{r}$$

Where

$\Delta\theta$: The resolution elements in angular direction

$\Delta\rho$: The resolution elements in logarithm of radius-direction

Δl : the arc length between neighboring points in the rectangular domain

Δr : the resolution element in the radius direction

r : the radius coordinate

The worst-case resolution in the log-polar domain is the minimum value of $\Delta\theta$ and $\Delta\rho$.

TEST DATABASE

At our institute a database of images is available of 432 drug tablets that have been submitted as a case to our institute. The database exists of drug tablets from 1992 until now. The database is available on line in QBIC implementation at http://forensic.to/drugstablets.

Furthermore, we have a test set of three drug tablets that have to be searched against. These tablets are acquired in different angles of rotation to determine if the algorithms are rotation invariant. In total we had 25 images for each tablet, so in total we have 432 + 75 images in the database. In figure 3 the three different tablets that we have selected are shown.

RECALL OF IMAGES IN THE DATABASE

If we look to the best search reduction we should only find the relevant images in the top position of our search, so we should filter ã[25]:

(8)

For the matching results there are also other measures available in literature (e.g. 17). However, for the experiments we will conduct we will show how many of the images are in the top position of the database and how far in the database the user should search before all images have been found for a particular image.

For the reason that it is not known if the color has been taken into account with the QBIC-database and the Imatch-database, we also compared the results based on color.

EXPERIMENTS

It is possible to implement many different Contents Based Image Retrieval Systems. In the scope of this article we limited the number of experiments, and tested the algorithms and software for the test images.

Figure 25: Test images used for the comparison of algorithms (from left to right: Bacar / Mitsubishi / Playboy)

6.1 Plain images

We have tested the different methods with the plain images. The results are shown in Table 1. The first number in these tables is the number of hits in the top positions (25 means all of them). After this a percentage of the database is given that has to be searched until all images are retrieved.

Table 5a: Results with QBIC 3.0 version-database with plain image.

	color	layout	texture	special hybrid
Bacar	25; 5 %	25; 5 %	6; 42 %	25; 5%
Mitsubishi	25; 5 %	8; 14 %	3; 22 %	24, 8 %
Playboy	25; 5%	9; 19 %	15; 22%	22; 14 %

Table 5b: Results with Imatch version 2.1 -software with plain image

	color	layout
Bacar	25	25
Mitsubishi	25	8; 14 %
Playboy	25	9; 19 %

Table 5**c: Results with MPEG-7 algorithms (version as available from CVS-host o15 July 2000)**

Table 5d**: Log Polar comparison**

	Default
Bacar	25 ; 5 %
Mitsubishi	23 ; 7 %
Playboy	20; 12 %

From the tables we can determine that the MPEG-7 implementations do not work as well as the QBIC and Imatch implementations for these drug tablets. With the QBIC and Imatch-search systems, the lights conditions and color features are used. This explains the reason that all images were found in top positions. The Bacar-tablet has a purple color and there are not many other purple tablets in the database. For this reason this tablet correlates best with color descriptors. The log polar implementation works best on shape. However, this method takes much computing power (for searching the complete database it took several days on a Pentium II 333 Mhz –computer), and there are no indexes that can be easily searched though. For this reason we did pre-processing of the images.

7.5 Preprocessed Images

Since we would like to have more control on which part of the tablets are compared, it is

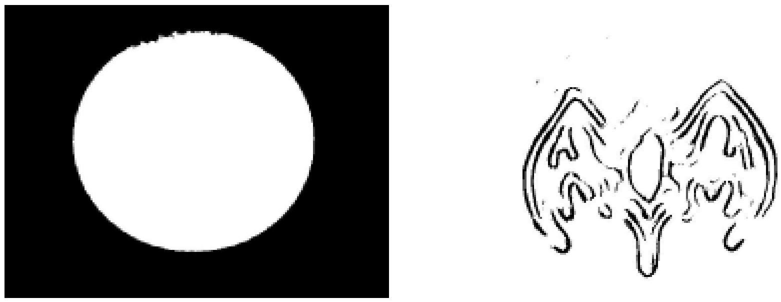

Figure 26: Splitting of shape of pill and logo with the algorithm described

necessary to segment the image itself in the logo part and the tablet part. The shape of the tablet is also a measure where it can be searched on; however, it is out of the scope of this paper. We segment the logo itself with a standard procedure. The procedure is as follows:

- First normalize the image, then threshold below grey-level 128
- *For finding the shape of the tablet*: label with Euclidean distance metric, 4 Connectivity, with a Split and Merge Factor of 14 percent, and a Minimum Region Size of 27 percent (these values are from analyzing several tablets)
- *For finding the edges of the tablet:* threshold
- *For filtering the edges of the tablet:* make the selection 5 percent smaller
- Then multiply the thresholded and resized image with the image (Figure 25, right)
- The final results is the logo (Figure 25, left)

In Tables 2a-c the results of this procedure are shown. The log polar method has not been tested with these images.

Table 6 a: Results with QBIC 3.0 version-database with plain image (the color search engine fails to operate for b/w images)

	color	layout
Bacar	failed	1 ; 55 %
Mitsubishi	failed	2 ; 75 %
Playboy	failed	1 ; 63 %

Table 6**b: Results with Imatch version 2.1 -software with plain image**

	Default	Fuzzy
Bacar	2; 80 %	4 ; 67 %
Mitsubishi	6 ; 77 %	10 ; 38 %
Playboy	3 ; 49 %	13 ; 28 %

Table 6**c: Results with MPEG-7 algorithms (versions as available from CVS-host of 15 July 2000)**

	ColHistNonUniS	Object Bounding Box	ContourShape	RegionShape
Bacar	1; 75 %	1 ; 33 %	25 ; 5 %	4 ; 22 %
Mitsubishu	1 ; 99 %	1 ; 68 %	24 ; 5 %	3 ; 22 %
Playboy	2 ; 45 %	1 ; 75 %	25 ; 5 %	1 ; 22 %

7.6 Conclusions and Discussion

In this research it appeared that the use of contour-based shape that was available in the MPEG-7 resulted in the most optimal results for speeds versus ranking on the hit list. This method uses the Curvature Scale-Space representation, which captures perceptually meaningful features of the shape. The log-polar implementation can also be used. However, this method takes a lot of calculating time, and for the searches no indexes can be calculated so the complete database has to be compared each time.

The color features appeared to work well with our test set. However, in practice this method is not useful since light conditions vary, and also the color of the tablet itself can differ with the same stamp.

The results of this research are limited to the three different test cases and the database of pills that have been used. It is expected that logos of pills that have been damaged severely will not be in the top position.

In future research 3D-images that are acquired by structured light equipment will be tested with different image search algorithms.

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8 Conclusion and Discussion

In this thesis an overview is shown on methods for automatic comparison of images. For databases of tool marks, cartridge cases, shoe prints and drugs pills several implementations have been made.

For the tool marks, the practical use of these databases is still limited. In the Netherlands there exist some databases of tool marks, however automatic comparison is not implemented, since it is difficult, due to the different shapes tool marks have. Several efforts have been made to implement automatic comparison of striation marks. However the results of these algorithms and the cost of labor are to high to implement a satisfactory system, as also can be seen in the bullet systems (IBIS).

The cartridge case systems are more promising, since they are widely used in practice. These systems have correlation engines, and modification to a 3D-system could result in better correlation ranks. In the Netherlands we use the system Drugfire, as is used by many agencies in the United States. The company that produces this product is phasing out the software, since there appeared to be patent infringement problems with the other company IBIS. In the United States, the IBIS system will be the standard. This system has a more reproducible way of imaging the cartridge cases, and better results are possible with this system. In practice, the system results in "cold" hits.

The shoe print systems are mostly used in the United Kingdom. The other systems could not survive in the market, since government forensic laboratories that develop these systems, develop them for themselves, and this means that they do not really want to market them. In the Netherlands we have seen some results with these systems, when used manually. Automatic classification and comparison is possible for clear shoeprints. In practice the problem with shoeprints is that they are often vague, and for that reason a human being should classify. Shoe prints are valuable in forensic science. They are time-consuming for comparison and collection, and it depends on the police region if they are used. In regions with much crime, we see

The drugs pill system is used, however since the number of drugs pills is limited, an automatic comparison algorithm is not very useful at the moment. In future, if more images are in the database, it could result in more need for such a logo comparison. The problem with shape comparison of these logo's is to filter out the images of the logo. Since the acquisition of images is with cheap camera systems, the quality of those images is limited, and this results in huge problems of splitting the logo's from the drugs pills with an image processing method.

Image systems in forensic science can help to solve crimes, however for the different databases there should be made a decision which databases are most cost effective. It is also the experience that databases can change the ways people commit crimes, as has been seen with fingerprints. More criminals wear gloves when committing a crime then before those systems were widely used.

New developments in this field will not only include faster systems, but also standardization of the implementation of new algorithms will take place in this field. In 2001 the MPEG-7 standard will be a standard for indexing images and video. This might have an impact on the way we search for video and audio on the Internet. A sketch generated by the user will be compared with a database of images.

It very much depends on the market of this framework of searching will be actually used. In future databases more powerful methods can be used, that require parallel processing. Furthermore the 3D-acquisition will result to better results, as long as the data acquisition is standardized.

In this research it appeared that several general approaches of searching in forensic image databases are applicable, however often they have to be modified in such a way, that they are focused on the kind of evidence. The human being is in general still much better in interpreting the separate images, compared to an algorithm.

The combination of Data Mining and using other kinds of data will result in relations between crimes, which were not considered before. Relations can be found that afterwards appear to be a coincidence and misleading, and sometimes they will really result that the case is solved.

The cellular phones that can be used to track people, combined with the information of phone numbers that people have called, can result in a way of reducing the number of images in a very efficient manner. Furthermore credit card and banking information combined with the loyalty programs of shops, are a way of reducing the number of possibilities between a crime scene and suspects. Wiretaps of the Internet used in an appropriate way also result in information about networks of people. The challenge with combining this information for forensic science, is however that privacy laws might conflict with the need to solve a case.

All these methods will however result that a criminal is more aware that traces can be found. In court they are confronted with the evidence. This evidence is all public, and the networks of criminals will be informed about new methods for solving crimes. The next issue is that they will try to alter the evidence in a way that another person is charged for the crime. This has been seen with criminals with cellular phones. Nowadays often the SIM-cards are not in the phone anymore if a criminal has been caught. SIM-cards contain much information about the last numbers called, phonebook and networks used. It also becomes more difficult to determine if a digital trace was really from the suspect. Since the person behind the computer, or the hacker breaking in the system, can be hard to distinguish.

Some of these systems have had too high expectations. For instance the shoe print system appeared to be too much work for the result they have. The same is true for the bullet part, where lots of time is spent on acquiring the images, however not many hits are found.

It remains important to analyze the results of the search and to have user feed back about the position that a certain image is found on the hit list.

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