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Content Based Information Retrieval in Forensic Image Databases

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ABSTRACT: This paper gives an overview of the various available image databases 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.

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

In forensic science, the importance of image databases has been known for years. The successful use of databases for fingerprints is an example of a very useful database. The use of fingerprints is still important, however, many suspects know that they can be identified by their fingerprints, and they take precautions. Nowadays, we see that DNA-databases are important in solving even old crimes. However, 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 are solved.

Many organizations have large databases and video collections in digital format that they would like to make accessible on-line. 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, many research groups are active. Databases of faces, logos, and other shapes are well known (QBIC (1), Photobook and Virage). In addition, fingerprint databases in forensic science have been heavily researched (16), whereas in forensic firearm investigation, the commercial systems (23) have shown the need for good and fast searching algorithms.

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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 the higher-level concept of the meaning of objects in the scene are clues for retrieving the correct images in the database.

The different aspects of an image should be covered. In forensic science, this means that one has to know what kind of comparisons should be done. Together with 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 that will work properly.

The need for visual information retrieval is more apparent nowadays since there exist many digital archives. The development in multimedia systems and the large-bandwidth computer networks have made the need for good tools for retrieving visual information.

Different types of information are associated with images and video (2):

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

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, then we will apply these methods to several forensic databases, each focusing on a different method of matching images. These databases are: tool marks, shoeprints, cartridge cases, and drugs/pills. Based on our experience with these databases and study from literature, we will conclude with final remarks.

Generations of Databases

In literature (2), databases are divided into different generations. In this research we will focus on second-generation databases.

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 into the database. Different users might enter different text descriptions into 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.

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 such 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 choosing a different image in the database as a sample, 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 other than that.

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

Most current research 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 (3).

Third Generation Visual Information Systems

These systems work in an "intelligent" manner, as the Human Visual System works. 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 on the understanding of the human visual system combined with acceptance by the users.

Visual Content

The current databases focus on visual content (4,5). In this section, a short overview is given of perceptual features of video and images. These are features such as color, texture, shape, and motion.

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 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. The color can be important for child pornography (skin color) or colors of drug pills.

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 striation marks or impression marks.

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, characteristic 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.

Another approach for shape representation is the shape through transformation approach. In the shape through transformation approach, a shape is a template and is deformed in order to improve the match with the target image. The amount of deformation needed is a measure of similarity.

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—a shape representation in the database invariant to geometric transformations such 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.

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 preselection of a database (selecting a part of the database) based on the contents.

Spatial Relationships

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

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 nonlinear equations. Motion might be important in future databases of gait of persons.

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 than would be for firearms. They have to be implemented in a database with interaction with experts.

Similarity Models

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

Metric Model

This model is frequently used for databases of features, since it is easily implemented. Several distance functions are commonly used (6): 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 (7) 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, which 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, which is represented in a point in a virtual space.

Other Models (8)

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 (9)—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 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.

Indexing Methods and Performance

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, such 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 there is often a need to search on image features based on a weight factor.

Performance

In document retrieval (10), the classification is performed using Table 1.

In documents, we have the recall and precision measures for evaluating the performance of a database.

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

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

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, and
- Computational complexity.

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

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 means deriving information from a specific scene. The actual process of the human brain is not known (11), 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 (12) are far from successful. Di-

TABLE 1—*The classification in document retrieval.*

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

viding the human abilities in smaller tasks and implementing them reveals promising results.

Biometric

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 or authenticating the person. For the biometric systems there are several requirements (13):

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. Collectability: the characteristics can be measured.

These systems might serve two goals: identification or recognition (14). Identification is the most difficult 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 (15) 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.

Fingerprints—Four major approaches have been taken for automatic fingerprint classification (16):

1. Syntactic: the ridge patterns and minutiae are approximated as a string of primitives. The predefined 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.

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, jewelry, 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, the face should be recognized in the image (17). 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 as to which approach will be appropriate.

One of the main problems with face recognition is dimensionality reduction to remove much of the redundant sampling (18). Sophisticated preprocessing techniques are required for the best results.

There are several methods for feature-based approaches, which require the detection and measurement of salient facial points. Approaches exist 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 (19), especially if shape and texture variations are considered as important parts 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 is very difficult.

Template matching involves the use of pixel intensity information. This can be in the original gray-level dataset or in preprocessed 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 (20)) 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. Variations in illumination can be compensated for with Gabor filters (21).

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 (22).

Despite the developments, it still is very hard to compare a database with photographs that are taken under various conditions (e.g., from visa request) with a high precision.

Handwriting—Different systems (23) of forensic handwriting comparison exist on the market. The oldest system is the Fish-system, which was developed by the Bundes Kriminal Amt in Germany. Another well-known system is 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: interline distance, and the inter-word distance. For each word, all letter heights are measured, as well as the slant and the word width. For Fish, the black/white statistics are also computed, and they will analyze upper and lower loops if available. These systems are used in practical cases, such as analyzing who might have written threatening letters.

Tool Marks—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 shape such as 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 Fig. 1 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 in which a casting is made with a gray silicon casting material. Subsequently, these images are stored in the database. The database is used for preselection, 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.

We examined tool marks, and 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 would be 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.

Automatic comparison is still difficult with tool marks, since a wide variety of them exist. Furthermore, it is often hard to reproduce them with test marks.

Cartridge Cases—DRUGFIRE (24) and IBIS (25,26,27,28) 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 (Fig. 2). 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 applied by Forensic Technology 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 gives the best matching results.

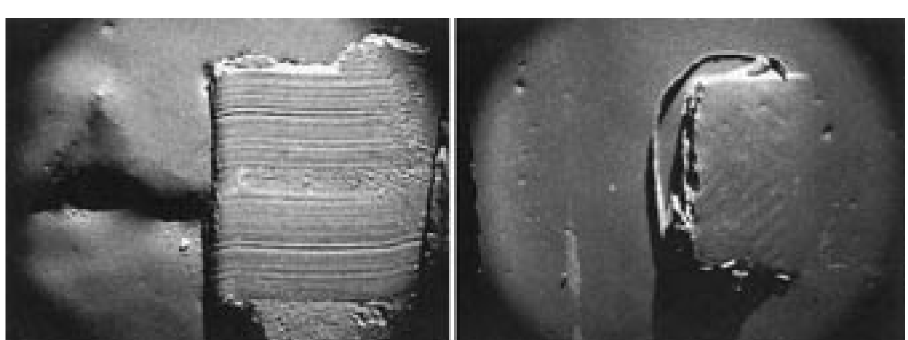

FIG. 1—*Images of striation and impression marks.*

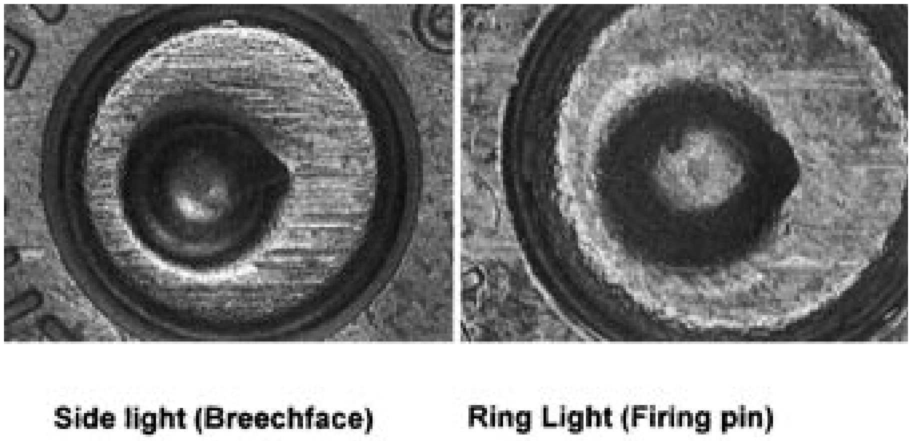

FIG. 2—*Ring light and side light images of impression marks on a primer of a cartridge case.*

Other systems that have been described on the market are the system Fireball (29), 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 (30) or by fusing the images with different angles of coincidence are described in the literature (31). Since the firearm examiner is used to comparing side light images and not three-dimensional images, development and acceptance of 3D-image matching methods progress slowly. Therefore, this research is focused on the matching of side light and ring light images.

From our research (32) it appears that in cases where the positioning and the light conditions among the marks in the cartridge cases were 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"-multi-resolution 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 preselection. 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. An example of this damage is text imprints in the firing pin.

These databases are widely used in practice, and they appear to solve cases much faster than with a manual system. If used in a network, crimes can be solved much faster than in the past.

Shoeprints—Shoeprints can be valuable as evidence, since they are often difficult to hide. The fine scratches in outsoles can be used to identify a shoe print. A database of shoes of suspects in comparison with a database of shoe prints can be valuable for solving crimes. Often the out sole design has to be classified for the shapes that are visible in the design. We have tested several algorithms (with neural networks (33)) for classifying these prints automatically, since different examiners who enter the shoes into the database will classify them in a different way. For shoeprints, it is very hard to do automate this; however, for outsole designs of shoes it is possible, as long as the classification matrix is not too complicated. The shape comparison methods for image databases are useful for these kinds of databases.

Currently, the shoeprint databases are—in general—rarely used. However, some police regions use these databases as first-generation databases. Searching in the databases on content is still a difficult task, since shoeprints are often blurred. This requires the examiner to do much of this work manually.

Drug Tablets—At the drugs department of our institute, 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 are 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 (Fig. 3).

FIG. 3—*Logo on drug tablet.*

In our research (34) it appeared that the use of a 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 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.

The first-generation database is used, and a second-generation database is available on the Internet.

Discussion

New developments in this field will not only include faster systems, but also standardization of the implementation of new algorithms will take place. 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.

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

For some databases, it is still difficult to get a high precision. A database of shoeprints and toolmarks often contain much blur, and for this reason it is very hard to do preprocessing. Databases of faces are also difficult to manage, since often the images are not taken under standardized circumstances.

Moreover, the databases can be useful for getting relevant statistical data of the forensic evidence types, especially where the marks are used for identification. Several databases of new kinds of forensic evidence (e.g., ear prints, nail striations) will be useful to prove the randomness of forensic features. If these databases are used in combination with other databases (DNA, fingerprints), more technical evidence is obtained in relation with how a crime has happened, and more cases can be solved.

Using optical processors (35,36) or parallel processors implemented in hardware is an option to improve speed of the image matching, compared to our brute force method.

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 evidence type. Forensic databases are also important for understanding the statistical relevancy of certain evidence. Other databases, such as databases of ears, will help the forensic community in drawing conclusions based on statistics in these databases.

It remains important to analyze the results of the search and to have user feedback about the position at which a certain image is found on the hit list. Third-generation databases (that do not exist yet) might also be useful for the more difficult kinds of image shapes.

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