AUTOMATIC CLASSIFICATION OF SHOEPRINTS FOR USE IN FORENSIC SCIENCE BASED ON THE FOURIER TRANSFORM

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ABSTRACT

This study developed a system of automatic classification of shoeprint images into groups belonging to the same sole pattern. When presented with an image of a new shoeprint the system displays a ranked sequence of shoeprint images from the database. The shoeprint images are ranked from best match to worst match in terms of the pattern of the shoeprint. For this study a database of 503 shoeprint images belonging to 139 pattern groups was established with each group containing 2 or more examples. The pattern grouping was performed by a panel of human experts. This designed system is a fully automatic method and functions with minimum user intervention. Tests of the system have shown that the first shoeprint image displayed is a correct match 54% of the time and that a correct match appears within the first 5% of displayed shoeprints 75% of the time. The system has translational and rotational invariance so that the spatial positioning of the new shoeprint images does not have to correspond with the spatial positioning of the shoeprint images of the database.

1. INTRODUCTION

Shoeprints are often found at crime scenes and can provide valuable forensic evidence. An image of the shoeprint can be obtained using photography, gel or electrostatic lifting or by making a cast when the impression is in soil. Subsequently in the forensic laboratory, the image of the shoeprint is compared with the soles and heels of shoes taken from suspects (if there are suspects) and with impressions made using those shoes. Bodziac [1] is one of the leading authorities in the area and describes the process of detection and recovery of footwear impression evidence and of comparison of the impressions with suspect shoes.

What happens when there is no suspect? Most modern shoes and trainers have patterns on their soles and heels and there are a wide variety of patterns on the market. The photograph of the impression or of the lifted impression or cast can be scanned and a digital image produced. Forensic analysis requires comparison of this image against specific databases. These databases include:

1. Database of impressions made by shoes currently and previously available on the market
2. Database of footwear impressions found at other crime scenes

The purpose of this comparison is two-fold. First, if the type of shoe, which made this impression, can be identified, this is of assistance to the investigating officer e.g. what brand of shoe to look for when searching a suspect's house. Secondly, a database search may reveal other crime scenes at which impressions of that type were found. An indication of a possible link between different scenes is useful information to the investigating officer as it may suggest possible suspects to him. If a suspect is eventually identified, his possible involvement in a number of offences can be explored and these offences may be solved.

A number of semi-automatic schemes have been proposed to assist forensic laboratories making these database comparisons.

G. Alexandre [2] proposed a semi-automatic scheme for classifying shoeprints from burglars. Each sole is described by a number of geometric patterns, which must be determined by a human expert. Examples of patterns include zig zags, circles, squares and letters. A database of known shoe types described using these geometric patterns was established and new (unknown) shoeprints could be compared to shoeprints in the database to try and find a match. A problem with this method is that no attempt is made to code the spatial information of the patterns and that modern shoes have increasingly more intricate sole patterns which are difficult and tedious to describe with a few basic shapes. Two other systems have been reported which use this semi-automatic method: "Shoe-Fit" by Sawyer et al [3] and "Shoe" by Ashley [4] are based on the idea of annotating the images – usually by selecting visible characteristics of the shoe sole, such as wavy patterns – concentric circles, logos etc.

Z. Geradts et al [5] describe an approach to an automated system. As above the sole pattern is described by a series of geometric shapes which can be entered by an expert or generated automatically using a number of

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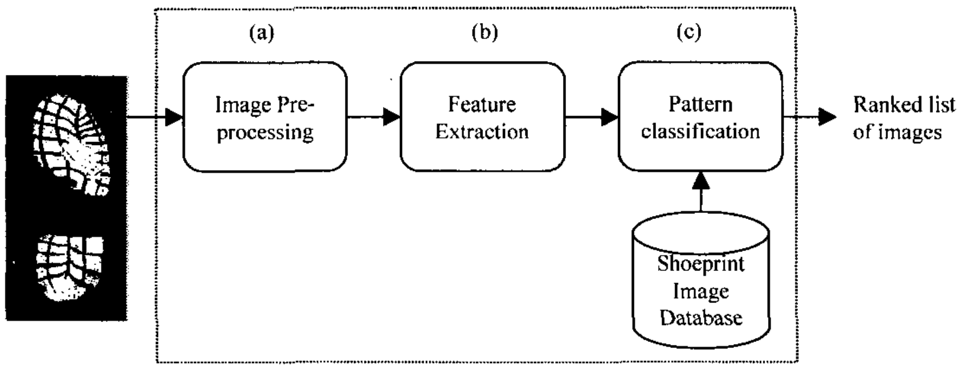

Figure 1: Shoeprint Analysis System

primitive 'erosion' and 'dilation' operators applied to a digital image of the shoeprint. The spatial position of these shapes is recorded. For each type of geometric shape the two-dimensional Discrete Fourier transform (2D-DFT) was used to determine the spatial frequency of the shapes. The advantage of the 2D-DFT is that it is invariant to translations. Classification was achieved with a neural network processing the Fourier transform coefficients. The authors do not report on the accuracy of their system.

Bouridane et al [6,7] describe an automated system which utilises fractals to represent the shoeprints. They report an accuracy of 88% in classifying 145 images. They tested the system for translational invariance and found that small translations (2-10 pixels) made little difference to the accuracy of the system. Their system does not attempt to answer the question of rotational or scale invariance.

2. AIM

The aim of this project was to develop a fully automatic shoeprint recognition system. While a number of schemes exist for semi-automatic shoeprint recognition systems, work in the area of automatic shoeprint recognition has not been reported widely. An important property of any scheme is that it must be able to properly process shoeprints that have been rotated, translated or scaled relative to the shoeprints recorded in the database.

3. SHOEPRINT DATABASE

A database of shoeprint images was formed by digitising 1276 paper images of shoeprints provided by the Forensic Laboratory, Garda HQ, Dublin, Ireland. The shoe wearers were exclusively male. Each paper image also contained information on the shoe manufacturer, style, size, the age of the shoe wearer and this was attached to each image of the database.

The 1276 shoeprint images were divided into categories where each category contained images with the same pattern. A panel of 3 experts was used for the process. It was established that there were 912 independent pattern categories with 773 categories containing one shoeprint and 139 categories containing two or more examples of shoeprints with the same pattern. The 503 shoeprint images comprising the latter 139 categories were used for validating the algorithm.

4. METHODS

The algorithm developed consists of three main units outlined as shown in Figure 1. The sections are explained in turn.

(1) Image Pre-processing. The input scanned shoeprint images are subjected to many distortions in both the imprint process and the scanning process. Distortions include rotations, translations, scaling and additive noise. The aim of the pre-processing stage is to reduce these distortions, and convert the image file into a standard size than can be passed to the feature extraction stage. The various steps are displayed in Figure 2.

The input images are approximately 4200x2700 pixels, although differing slightly in size. This is an over sampling of the underlying frequency content in the patterns in the images. To avoid excessive computation, the images are down sampled by a factor of 16.

In order the extract the actual shoeprint from the other elements of the image, namely the background noise and the black borders, the image is thresholded. After experimentation, the optimal threshold point was found to

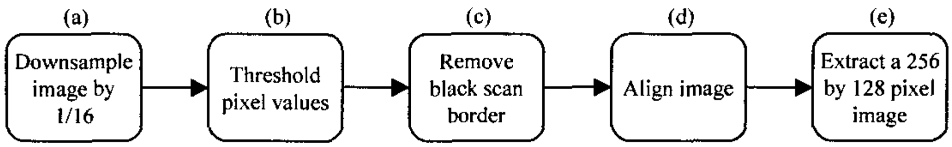

Figure 2: Image pre-processing steps

be 230. This means pixel values below this are set to 255 (black), those above set to 0 (white).

The black border created in the scanning process is removed by finding the largest connected component of 0 value pixels. All the pixels in this component are then set to 255.

The centroid and major axis (minimum inertia axis) of the resulting image are then computed. The image is then rotated about the centroid so that the major axis is parallel to the y-axis.

The final down-sampled image is the 256x128 pixel block that contains the maximal number of 0 value pixels in the image. The final processed image is ready for further processing by the feature extractor stage.

(2) Feature Extraction. The features extracted from the processed images are the 2-D DFT coefficients. These coefficients represent the levels of different spatial frequencies within the entire image. These spatial frequencies in turn provide a description of the pattern contained in the image.

(3) Pattern Classification. In order the compare an input image with an image in the database, a measure of similarity between the two sets of features extracted from the images was required. The larger the measure of similarity between the input image and the database image, the more similar the two images are. An input image is compared to all images in the database and the similarity measure calculated for each comparison is used to rank the images in the database from most similar to least similar. The database images are shown in ranked order to a human expert who can select the final database image that best matches the input image. Thus our system acts a *screener* for the human expert i.e it presents to the expert the images that are most likely to match the input image first. A human expert can confirm the final matching from the ranked list.

Two similarity measures were considered in this project. In the following d_i is the measure of similarity between an input image and the *ith* image in the database. I_i is 128 by 256 matrix of image pixel values of the pre-processed database image.

I_m is a 128 by 256 matrix of image pixel values of the pre-processed input image.

DFT is the Discrete Fourier transform.

The first is a simple Euclidean distance of the difference of two sets of 2-D DFT coefficients:

$$d_i = -\sum_{j=1}^{128}\sum_{k=1}^{256}\left[\left(abs\left(DFT\left(I_m\right)\right)\right)-\left(abs\left(DFT\left(I_i\right)\right)\right)\right]_{jk} \quad (1)$$

where *abs* is the absolute value function.

The second similarity measure uses the correlation coefficient between the 2-D DFTs of the two images.

$$d_i = corr2\left(DFT\left(I_m\right), DFT\left(I_i\right)\right) \quad (2)$$

where *corr2* is the 2-D correlation function.

The advantage of this similarity measure is that it is invariant to the *pressure* of the print. So a 'heavy' print and a 'light' print will still have a high similarity measure even though the heavy print will contain many more black pixels.

5. RESULTS AND DISCUSSION

The 503 shoeprints were used to test the algorithm using a cross-validation scheme. In turn, each of the selected 503 shoeprint images was withdrawn from the database and the system used to compare the shoeprint against the remaining 502 shoeprint images. From each of these trials a ranked list of images was produced and the rank of the first shoeprint image that was from the same pattern category as the withdrawn image determined.

Ideally an image from the same pattern category would be ranked first every time. Using this method it was only possible to use the shoeprint images from pattern categories with two or more examples as this ensured that there was at least one matching print in the database for each withdrawn shoeprint image. From these results the probability of our algorithm in correctly identifying a matching shoeprint within the first N ranked images was calculated. The probability is defined as the proportion of times during the 503 trials an image in the first N ranked images was from the same pattern category as the image being matched. The results for the two similarity measures are shown in Figure 3.

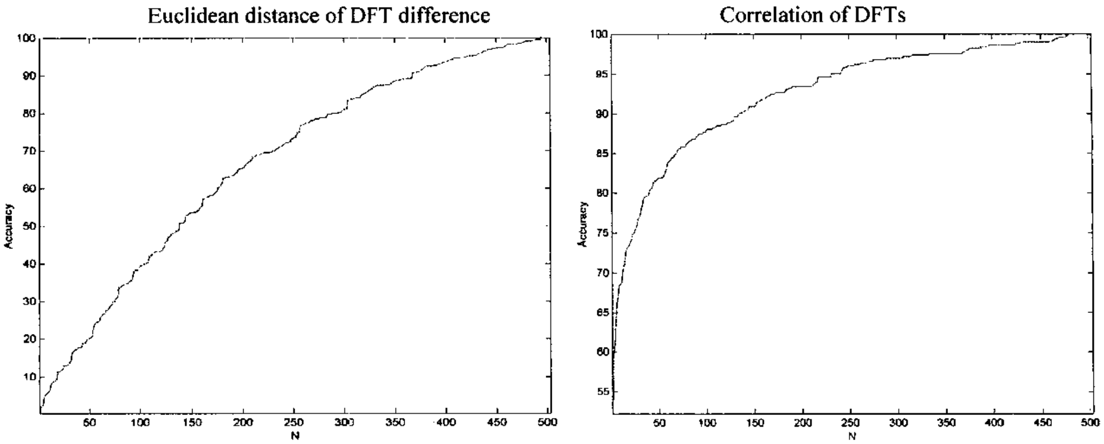

Figure 3: Probability (accuracy) of the algorithm in correctly providing a shoeprint image from the same pattern category as the input image as a function of 'N'.

Figure 3 demonstrates that the similarity measure using the correlation of the DFTs results in much better classification performance than the Euclidean distance of DFT difference. The correlation of the DFT method ranks first (N=1) a shoeprint image from the same pattern category as the input image 54% of the time and ranks a shoeprint image from the same pattern category as the input image somewhere in the first 5% matches (N=25, shown with dotted line) 75% of the time. As N increases the probability of providing a shoeprint image from the same pattern category increases and at N=503 the probability is 100%. It is worth noting that if we were to randomly guess which of the above 139 categories an input shoeprint image belongs to, we would be correct on average 1 in 139 guesses or 0.72% of the time.

6. CONCLUSION

This study developed a system of automatic classification of shoeprint images into groups belonging to the same sole pattern. Tests of the system have shown that the first shoeprint image displayed is a correct match 54% of the time and that a correct match appears within the first 5% of displayed shoeprints 75% of the time. The system has translational and rotational invariance so that the spatial positioning of the new shoeprint images does not have to correspond with the spatial positioning of the shoeprint images of the database.

7. REFERENCES

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