AUTOMATIC RECOGNITION OF PARTIAL SHOEPRINTS BASED ON PHASE-ONLY CORRELATION

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ABSTRACT

In this paper, a method for automatically recognizing partial shoeprint images for use in forensic science is presented. The technique uses the Phase-Only Correlation (POC) for shoeprints matching. The main advantage of this method is its capability to match low quality shoeprint images accurately and efficiently. In order to achieve superior performance, the use of a spectral weighting function is also proposed. Experiments were conducted on a database of images of 100 different shoes available on the market. For experimental evaluation, test images including different perturbations such as noise addition, blurring and textured background addition were generated. Results have shown that the proposed method is very practical and provides high performance when processing low quality partial-prints. The use of a weighting function provides an improvement in the recognition rate in particularly difficult cases.

Index Terms— Shoeprint recognition, partial shoeprints, phase-only correlation, spectral weighting function.

1. INTRODUCTION

Shoeprints are routinely left at crime scenes and can be used as scientific evidence in forensic science. However, a large number of Scene of Crime (SoC) shoeprints are partial, due to incomplete contact between the sole of the shoe and the surface. They have generally very low quality: noisy, possibly blurred and/or with a non-uniform background.

A forensic investigator may use shoeprint images to perform different tasks:

i) Comparing the SoC shoeprint image against a database of marks made by shoes available on the market (to determine the make and model of the shoe).

ii) Matching the SoC shoeprint with other shoeprints taken from other SoCs (to link between crimes).

iii) Comparing the SoC shoeprint with shoeprints taken directly from suspects' shoes.

In order to assist forensic investigators in performing these tasks, some work in the area of automatic classification and recognition of shoeprints has been reported. Geradts et al. [1] developed an algorithm for the automatic classification of shapes in a shoeprint. They used Fourier features, invariant moments and neural networks. Their method works well for simple shapes (triangles, circles), but it fails considerably with more complex ones. Alexander, Bouridane and Crookes [2], [3] developed a technique for the detection and classification of shoeprints based on fractal geometry. Tests on low quality shoeprints using this technique have not been reported. Chazal et al. [4] developed a system based on the Fourier Transform where the Power Spectral Density (PSD) coefficients of the image are calculated using the Fourier Transform and used as features. The measure of similarity considered was the correlation of the PSD coefficients. The system was tested only on clean shoeprints. Our proposed new technique is based on Phase Only Correlation which captures more discriminative information when compared to amplitude based methods. Experiments clearly show that the proposed method outperforms the above existing ones.

2. PHASE-ONLY CORRELATION

In the Fourier domain, the phase information is much more important than the magnitude in preserving the features of image patterns, as proved by Oppenheim et al [5]. A simple illustration for shoeprint images is given in fig. 1.

Consider two images $g_1(x,y)$ and $g_2(x,y)$. The Fourier transform of g_1 and g_2 are $G_1(u,v)=A(u,v)e^{j\phi(u,v)}$ and $G_2(u,v)=B(u,v)e^{j\theta(u,v)}$ where $A(u,v)$ and $B(u,v)$ are amplitude spectral functions while $\phi(u,v)$ and $\theta(u,v)$ are phase spectral functions, respectively. The phase-only correlation function $q_{g_1g_2}(x,y)$ of the two images g_1 and g_2 is defined as:

$$q_{g_1g_2}(x,y) = F^{-1}\left\{\frac{G_1(u,v)G_2^*(u,v)}{\left|G_1(u,v)G_2^*(u,v)\right|}\right\} \quad (1)$$

$$= F^{-1}\left\{e^{j(\phi(u,v)-\theta(u,v))}\right\} \quad (2)$$

where F^{-1} denotes the inverse Fourier transform and G_2^* is

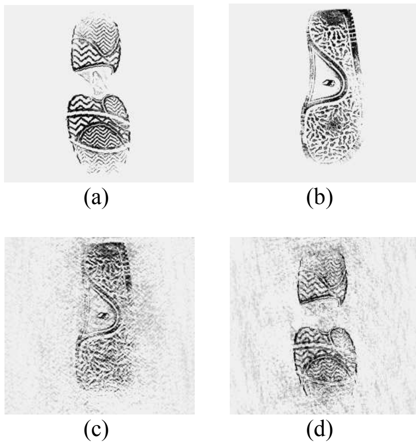

Fig. 1. (a) Original shoeprint image A. (b) Original shoeprint image B. (c) Image synthesized from the Fourier transform phase of image B and the magnitude of image A. (d) Image synthesized from the Fourier transform phase of image A and the magnitude of image B.

the complex conjugate of G_2. The term $Q_{g_1 g_2}(u,v) = e^{j(\phi(u,v)-\theta(u,v))}$ is called the cross-phase spectrum between g_1 and g_2 [6].

If the two images g_1 and g_2 are identical, their POC function will be a Dirac δ-function centered at the origin and having the peak value 1. When matching similar images, the POC approach produces a sharper correlation peak compared to the conventional correlation as shown in Fig. 2.

2.1. Translation and brightness properties of the POC function

Consider an image g_3 that differs from g_2 by a displacement (x_0,y_0) and a brightness scale a>0. Then, g_3 and g_2 will be related by

$$g_3(x,y) = a g_2(x - x_0, y - y_0) \tag{3}$$

In the frequency domain, this will appear as a phase shift and a magnitude scaling:

$$G_3(u,v) = a e^{-j2\pi(x_0 u + y_0 v)} G_2(u,v) \tag{4}$$

According to (1), (2) and (4), the POC function between g_1 and g_3 is given by:

$$q_{g_1 g_3}(x,y) = F^{-1}\left\{ e^{-j2\pi(x_0 u + y_0 v)} e^{j(\phi(u,v)-\theta(u,v))} \right\} \tag{5}$$

$$= q_{g_1 g_2}(x - x_0, y - y_0) \tag{6}$$

Equation (6) shows that the POC function between g_1 and g_3 is only a translated version of the POC function between g_1 and g_2. The two POC functions have the same peak value witch is invariant to translation and brightness change.

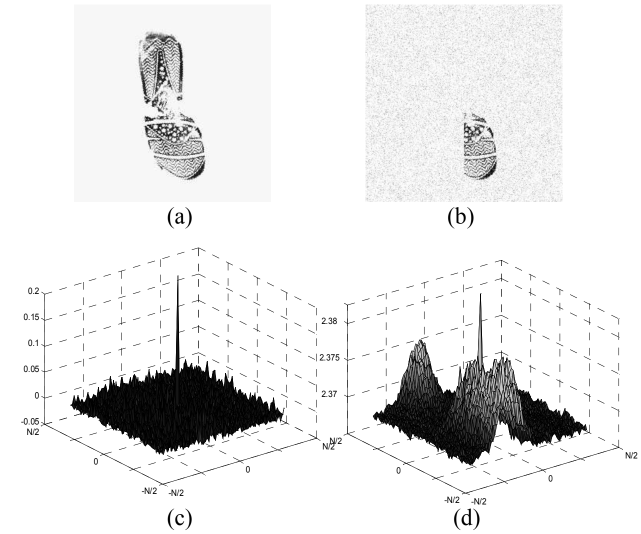

Fig. 2. (a) Original shoeprint image A. (b) Noisy partial shoeprint B generated from A. (c) POC between A and B. (d) Conventional correlation between A and B.

3. THE PROPOSED METHOD

The proposed method used the POC approach combined with a spectral weighting function.

3.1. Spectral weighting function

Spectral weighting functions have already been used with the POC technique in image registration in order to enhance the registration accuracy [6]. In this work, we propose to use a band-pass-type spectral weighting function to improve the recognition rate by eliminating high frequency components which have low reliability, without significantly decreasing the correlation peak sharpness as very low frequency components will be also eliminated. The proposed weighting function $W(u,v)$ has the same shape as the spectrum of a Laplacian of Gaussian (LoG) function and is given by

$$W(u,v) = \left(\frac{u^2+v^2}{\alpha}\right) e^{-\frac{u^2+v^2}{2\beta^2}} \tag{7}$$

where β is a parameter that controls the function width and α is used for normalization only. Thus, the modified phase-only correlation (MPOC) function $\tilde{q}_{g_1 g_2}(x,y)$ of images g_1 and g_2 is given by:

$$\tilde{q}_{g_1 g_2}(x,y) = F^{-1}\left\{ W(u,v) \frac{G_1(u,v) G_2^*(u,v)}{\left| G_1(u,v) G_2^*(u,v) \right|} \right\} \tag{8}$$

The peak value of the MPOC function $\tilde{q}_{g_1 g_2}(x,y)$ is also invariant to translation and brightness change.

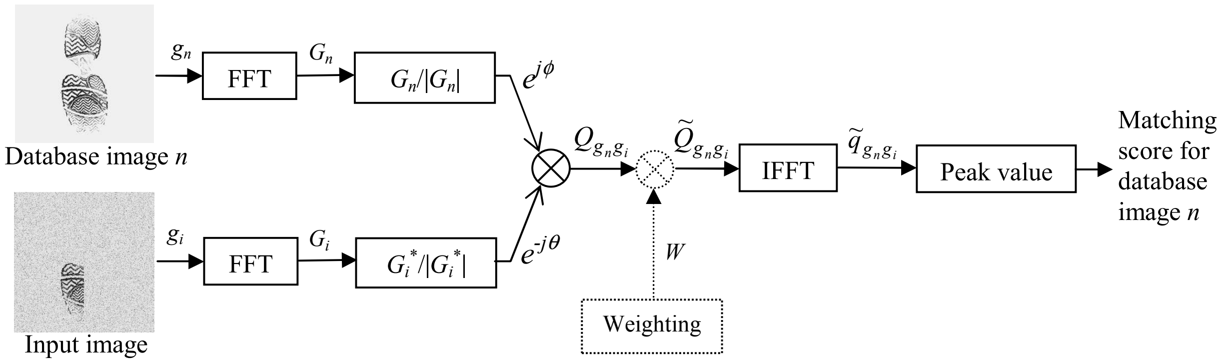

Fig. 3. Schematic of the proposed matching algorithm

3.2. Shoeprints matching algorithm

A schematic of the proposed shoeprint matching algorithm is shown in figure 3. In response to an unknown shoeprint image g_i, the algorithm matches g_i to each database image g_n (n=1…M where M is the size of the database) and determines the corresponding matching score. The matching algorithm consists of the following steps:

i) Calculate the Fourier transform of g_i and g_n using the FFT (Fast Fourier Transform) to obtain G_i and G_n.

ii) Extract the phases of G_i and G_n and calculate the cross-phase spectrum $Q_{g_n g_i}$.

iii) Calculate the modified cross-phase spectrum $\widetilde{Q}_{g_n g_i}$ by modifying $Q_{g_n g_i}$ using the spectral weighting function W.

iv) Calculate the inverse Fourier transform of $\widetilde{Q}_{g_n g_i}$ using the IFFT (Inverse FFT) to obtain the MPOC function $\widetilde{q}_{g_n g_i}$.

v) Determine the maximum value of $\widetilde{q}_{g_n g_i}$. This value will be considered as the matching score between images g_i and g_n.

The use of the band-pass-type weighting function W (defined in equation (7)) will eliminate meaningless high frequency components without significantly affecting the sharpness of the correlation peak (since very low frequency components will be also attenuated).

In this work, we have considered the peak value of the MPOC function as similarity measure for image matching, if two images are similar, their MPOC function will give a distinct sharp peak, if they are dissimilar, then the peak drops significantly.

After matching the input image g_i with all database images, using the algorithm describe above, the resulting matching scores are used to produce a list of m shoeprints (m<<M) from the database, ranked from the best match (with the highest matching score) to the worst (the lowest matching score). This list can be reviewed later by a forensic scientist to determine the correct match visually.

4. EXPERIMENTAL RESULTS

The algorithm was extensively tested using a database containing 100 complete shoeprint images (256 gray scale images of size 512x512) with good quality and uniform background, provided by Foster & Freeman Ltd [7]. To evaluate the robustness of the method to different alterations, 64 test images were generated from each original shoeprint image, giving a total of 6400 test images. The test images were grouped into 4 main sets:

Set1- contains 400 clean partial shoeprint images obtained by dividing each original complete shoeprint (from the original database) into four quarters: i) left toes and midsole, ii) right toes and midsole, iii) left heel and iv) right heel.

Set2- contains 2000 noisy partial shoeprint images obtained by adding a white Gaussian noise (with zero mean and standard deviations σ = 20, 40, 60, 80 and 100) to each partial shoeprint image from *set1* (using the MATLAB function '*imnoise*').

Set3- contains 2000 blurred partial shoeprint images obtained by blurring each partial shoeprint image from *set1*. We considered a motion blur of length L (L=10, 20, 30, 40, 50 pixels) and angle θ=90 degrees (vertical blur) to simulate shoeprint blurring caused by foot slippage in the real world. The MATLAB functions '*fspecial*' and '*imfilter'* were used to generate the blurred images.

Set4- contains 2000 partial shoeprint images with textured background obtained by pasting each partial shoeprint image from *set1* into five texture images of size 512x512. The texture images come from the Brodatz album [8], and are: D16 (Weave), D19 (Wool), D24 (Leather), D68 (Wood) and D94 (Brick).

During the evaluation process, each test image was used as input to the algorithm and matched against all 100 original images and the rank of the correct match determined. This process was performed 6400 times. Then, for each type of perturbations, the proportion of times during tests a correct match appeared first (first rank recognition) is determined.

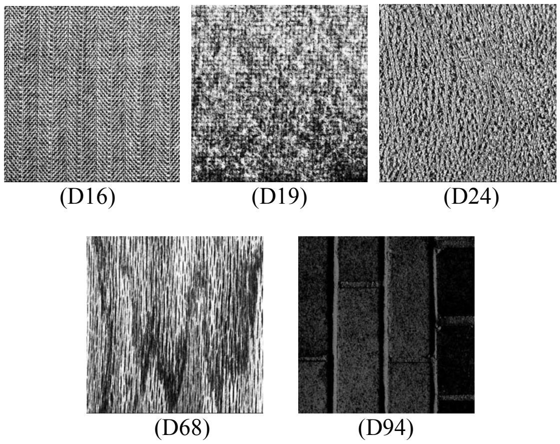

Fig. 4. Texture images used for generating test images in *Set4*

In order to compare our method to the PSD based algorithm [4], and since the database used in [4] was not available, the PSD based algorithm was also implemented and tested using the same procedure as the proposed method. The results obtained are shown in table I. MPOC and POC denote the phase only correlation algorithms with and without the spectral weighting function, respectively. The parameters of the weighting function used during the tests are β=10, 20, 30, 40, 50 and 60, with $\alpha = 4\pi\beta^4$ (to normalize the maximum of the MPOC function to 1: when matching two identical images). Only results corresponding to β=40, 50 and 60 (the best values) are shown in table I.

From these results, it can be seen that the phase based algorithms (POC and MPOC) outperform the PSD based one even without the use of the spectral weighting function. It can be also observed that the PSD based algorithm is very sensitive to blur and textured background. For the phase based approaches, the use of the weighting function (MPOC algorithm) introduced a maximum improvement of 4.5% of the recognition rate for blurred images without affecting the performance of the method when processing clean, noisy or textured background images. The best results were obtained for a weighting function with β=50, where 100% of the time a correct match was ranked first for all test images.

5. CONCLUSION

This paper has presented a new method for the automatic matching of shoeprint images based on Phase-Only Correlation. The algorithm developed has very high performance when processing low quality partial shoeprints and out perform the PSD based algorithm. As future work, we propose to use larger databases and to test the proposed method on real world scene of crime shoeprints. Rotation and scale normalization of images before the matching process will be also investigated.

TABLE I. First rank recognition rate (%) using PSD [4], POC and MPOC based algorithms.

Algorithms / Test images		PSD [4]	POC	MPOC β=40	MPOC β=50	MPOC β=60
1.Clean partial prints		96.25	100	100	100	100
2. Noisy partial prints	**σ=20**	95.75	100	100	100	100
	σ=40	93.5	100	100	100	100
	σ=60	88.5	100	100	100	100
	σ=80	76.5	100	100	100	100
	σ=100	60.75	100	100	100	100
3. Blurred partial prints	**L=10**	28.5	100	100	100	100
	L=20	13.25	100	100	100	100
	L=30	13	100	100	100	100
	L=40	13	97.75	100	100	100
	L=50	9.75	95.5	99	100	99.5
4. Partial prints with textured background	**D16**	13	100	100	100	100
	D19	4	100	100	100	100
	D24	1.25	100	100	100	100
	D68	5.5	100	100	100	100
	D94	64.5	100	100	100	100

6. REFERENCES

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