PP-RIDER: A ROTATION-INVARIANT
DEGRADED PARTIAL PALMPRINT RECOGNITION TECHNIQUE

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ABSTRACT

Matching degraded partial palmprint images against full palmprints is a challenging problem, since these images may be arbitrarily rotated, incomplete and often noisy. Such partial palmprints can be recovered from the palm impressions left on some surface (called latent partial palmprints) or can be generated, for testing purposes, by cropping full palmprints into different regions/segments (called synthetic/ pseudo latent partial palmprints).

This paper proposes a new technique, PP-RIDER – Partial Palmprint Rotation-Invariant and DEgraded Recognition, for recognizing degraded partial palmprints, which combines the Fourier-Mellin Transform (FMT) with the Modified Phase-Only Correlation (MPOC) technique. FMT is used to correct the arbitrary rotation of partial palmprints. Then, the concept behind MPOC is used for matching the degraded, but aligned, partial palmprint to a full palmprint registered in a database. Experimental results, using the THUMPALMLAB high resolution palmprint database, from which partial palmprints were cropped, randomly rotated and further degraded by adding white additive Gaussian noise and motion blur, show an improvement in comparison to the original MPOC technique.

Index Terms— Biometric recognition, degraded partial palmprint, latent palmprint, Fourier-Mellin Transform, Phase-Only Correlation.

1. INTRODUCTION

The usage of the palmprint as a biometric trait has been considered as good candidate for personal verification or identification, as it contains many useful and unique features such as principal lines, wrinkles, ridges, minutiae and singular points [1,2].

Most of the research conducted on the topic in recent years focused mostly on low resolution (about 100 ppi) full-to-full palmprint matching. The driver behind such research was to allow the usage of low cost image acquisition

sensors, small memory storage requirements and a reduced computational power, to enable the development of biometric systems for commercial applications (e.g., for access control) [3,4,5,6,7,8].

However, for forensic applications, high resolution (about 500 ppi) palmprints are required and partial palmprint matching must be supported [9]. Such partial palmprints could be either recovered from palm impressions left at crime scenes – also called latent palmprints – or, for testing purposes, they can be generated from live-scan high resolution full palmprints by cropping them into different regions/segments. The latter are also called pseudo latent partial palmprints, or synthetic latent partial palmprints, depending on whether noise/degradation are added or not, respectively [9,10]. Degraded partial palmprint matching is not a trivial task, since these images are often unstructured in shape and do not exhibit clear reference points that can be used for an efficient matching [11].

An initial report on latent palmprint matching was published by Jain et al. [10] in 2008. Synthetic and pseudo latent databases were built and Scale-Invariant Feature Transform (SIFT) and minutiae extraction techniques were used. Later, in 2009, Laadjel et al. [12] reported that recognition systems using SIFT and minutiae features presented a number of disadvantages: (i) minutiae extraction is difficult in poor quality images and (ii) the huge number of SIFT keypoints makes the system impractical. The Modified Phase-Only Correlation (MPOC) technique was then proposed [12] and tested on a pseudo latent database. Still in 2009, Jain et al. [9] proposed a new palmprint enhancement technique and a new minutiae descriptor technique called MinutiaCode, which was tested on two sets of partial palmprints: live-scan partial palmprints and latent partial palmprints. Results on the live-scan partial palmprints were better than those obtained for the latent partial palmprints, notably due to the better image quality and larger image size. In 2010, Laadjel et al. [11] presented a new rotation invariant technique in which the palmprint images were first enhanced by using a conventional fingerprint enhancement technique [13]. However, results were presented for non-degraded palmprint images.

Looking at the available literature, the need for a partial palmprint rotation-invariant recognition technique is identified; this technique should also be robust against

acquisition noise and different types of degradations. Therefore, in this paper MPOC is further modified by combining it with the Fourier-Mellin Transform (FMT) technique [14,15], to propose the PP-RIDER – Partial Palmprint Rotation-Invariant and DEgraded Recognition technique.

The remainder of the paper is organized as follows. Section 2 describes the original MPOC and in Section 3 the proposed PP-RIDER technique is described. Experimental results and their discussion are presented in section 4 and conclusions are drawn in section 5.

2. MODIFIED PHASE-ONLY CORRELATION

The MPOC technique is a modified version of the original Phase-Only Correlation (POC) [16]. POC is a correlation based technique which has been successfully applied in different biometric recognition applications, for instance using the palmprint [17], the fingerprint [18] or the iris [19]. It exploits the phase component of an image's Fourier Transform, as it has been shown to contain more information than the amplitude component [12]. POC's success is due to some of its important properties, such as: (i) translation invariance, (ii) immunity against noise, and (iii) brightness invariance.

POC can be calculated as follows. Let $f(x,y)$ and $g(x,y)$ be two palmprint images of the same size. Their 2D Discrete Fourier Transforms (DFTs), in the polar form, can be written as: $F(u,v) = Mag_1(u,v)e^{i\theta_1(u,v)}$ and $G(u,v) = Mag_2(u,v)e^{i\theta_2(u,v)}$, respectively, where $Mag_1(u,v)$ and $Mag_2(u,v)$ are the amplitudes (or magnitudes), and $\theta_1(u,v)$ and $\theta_2(u,v)$ are the corresponding phase components. Therefore, the normalized cross-power spectrum, $P_{f,g}(u,v)$, between these two images can be defined as

$$P_{f,g}(u,v) = \frac{F(u,v) \times G^*(u,v)}{\left| F(u,v) \times G^*(u,v) \right|} = e^{i(\theta_1(u,v) - \theta_2(u,v))}, \quad (1)$$

where $G^*(u,v)$ is the complex conjugate of $G(u,v)$.

The POC function [16], $poc_{f,g}(x,y)$ is the 2D Inverse Discrete Fourier Transform of $P_{f,g}(u,v)$, given by

$$poc_{f,g}(x,y) = FT^{-1}(P_{f,g}(u,v)). \quad (2)$$

This produces a sharp peak in the correlation plane when performing a genuine user matching attempt, while that peak drops significantly for impostor matchings.

Laadjel et al. [12] further modified this technique to make it even more robust the noise, by proposing the MPOC technique. A new peak measurement value, $mpoc_{f,g}$ is introduced as the ratio between the highest peak value in an area of size 11×11, the *inside − lobe*, centered at the origin

(or at the highest peak) and the highest peak value in the remaining area of the correlation plane, the *outside − lobe*, expressed as

$$mpoc_{f,g} = \frac{\arg\max\left(inside - lobe\left(poc_{f,g}(x,y)\right)\right)}{\arg\max\left(outside - lobe\left(poc_{f,g}(x,y)\right)\right)}. \quad (3)$$

The main idea of using this ratio is to increase the reliability of the peak discrimination in the presence of noise.

If a partial and a full palmprint aligned images belong to the same user, a distinctively sharp peak will be observed in the correlation plane and, thereby, a higher *mpoc* value will be observed, as illustrated in Figure 1 (a), (b), (e) and (f). Otherwise, the height of the main peak, as well as the *mpoc* value, drops significantly, as illustrated in Figure 1 (a), (c), (g) and (h). In addition, Figure 1 (a), (d), (i) and (j) show MPOC's strong immunity against additive Gaussian noise.

Hence, *mpoc* is a suitable metric to use as a similarity score for palmprint matching.

3. THE PROPOSED PP-RIDER TECHNIQUE

The proposed recognition methodology, PP-RIDER – Partial Palmprint Rotation-Invariant and DEgraded Recognition, aims at further improving the MPOC performance, notably in the presence of arbitrary rotations of the partial palmprints.

PP-RIDER consists of two steps: first, FMT is used to correct the random rotation of a probe partial palmprint with respect to a registered full palmprint, against which recognition is being attempted. Then, MPOC is used for matching purposes, applying it to the aligned images.

FMT [14,15] is an image registration technique which matches images that are translated, rotated and scaled with respect to one another in the Fourier domain. The PP-RIDER technique explores properties of the FMT allowing the alignment of randomly rotated images.

For instance, if an image $f_2(x,y)$ is a translated and rotated replica of image $f_1(x,y)$, with a translation (x_0, y_0) and a rotation θ_0, then
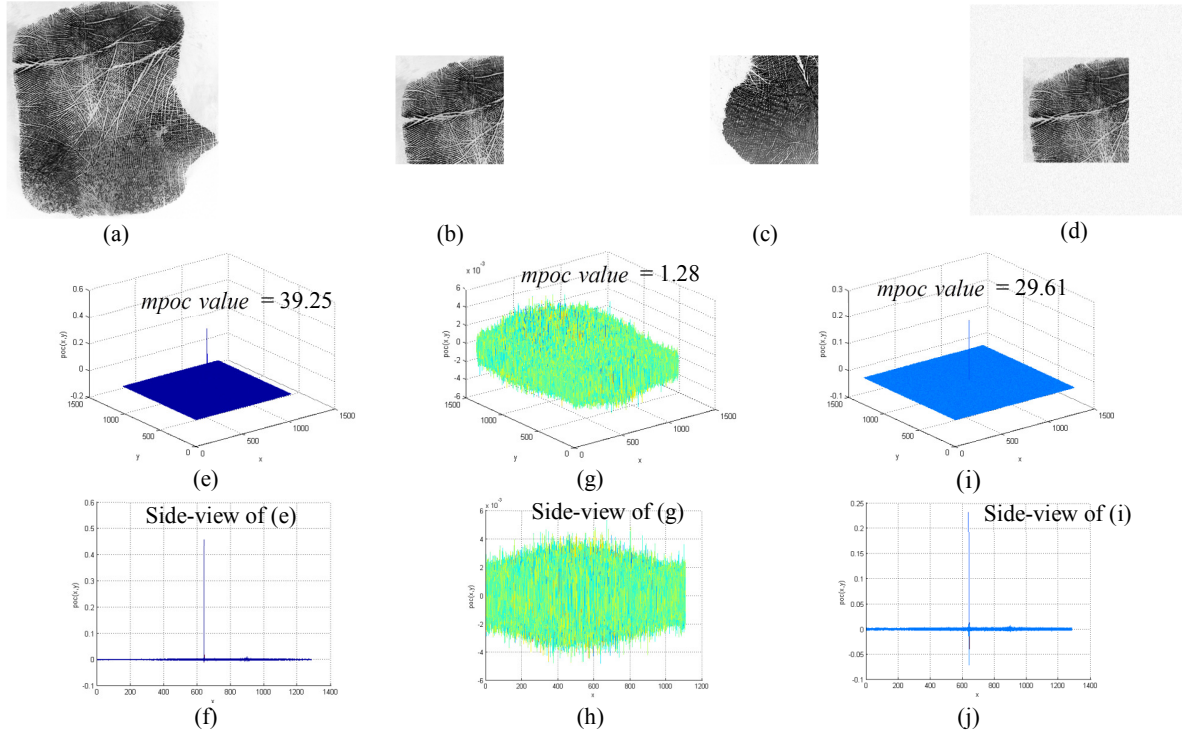
$$f_2(x,y) = f_1\begin{pmatrix} x\cos\theta_0 + y\sin\theta_0 - x_0, \\ -x\sin\theta_0 + y\cos\theta_0 - y_0 \end{pmatrix}. \quad (4)$$

Accordingly, the Fourier Transforms of $f_1(x,y)$ and $f_2(x,y)$ can be related as

$$F_2(u,v) = e^{-i2\pi(ux_0+vy_0)}F_1\begin{pmatrix} u\cos\theta_0 + v\sin\theta_0, \\ -u\sin\theta_0 + v\cos\theta_0 \end{pmatrix}, \quad (5)$$

$$Mag_2'(u,v) = Mag_1'\begin{pmatrix} u\cos\theta_0 + v\sin\theta_0, \\ -u\sin\theta_0 + v\cos\theta_0 \end{pmatrix}. \quad (6)$$

where Mag_1' and Mag_2' are the magnitudes of F_1 and F_2, respectively.

Figure 1: MPOC calculation without rotation; and in presence of noise: (a) – full palmprint image; (b) – partial palmprint extracted from (a); (c) – partial palmprint of a different palmprint image; (d) – (b) with Gaussian noise; (e) and (f), (g) and (h), (i) and (j) – Correlation planes between: (a) and (b); (a) and (c); and (a) and (d), respectively.

Moreover, Mag_2' is a rotated replica of Mag_1' and does not depends on the translation parameter (x_0, y_0). The above equation can be written in polar, or log-polar, coordinates as

$$Mag_2'(\rho, \theta) = Mag_1'(\rho, \theta - \theta_0), \qquad (7)$$

$$Mag_2'(\log \rho, \theta) = Mag_1'(\log \rho, \theta - \theta_0). \qquad (8)$$

The proposed technique uses equation (8) for computing the rotation angle θ_0, by using phase correlation. Check [15] for more details about FMT implementation.

Thus, from FMT the PP-RIDER technique incorporates the capability for determining the rotation parameter between a query and a registered image, also when dealing with probe images that correspond to only a fraction of the registered ones. And, from MPOC, it inherits the ability to perform well with partial palmprint matching, even in the presence of degradations, such as noise.

4. EXPERIMENTAL RESULTS

The proposed partial palmprint recognition technique has been tested using a large-scale, publically available, high resolution palmprint database: THUPALMLAB [20]. It contains a total of 1280 full palmprint images from 160 unique palms (80 subjects × 2 palms per subject × 8 full palmprint images per palm). The greyscale images were acquired using a commercial Hisign palmprint scanner, their original size being 2040 × 2040 pixels, with a 500 ppi resolution. The images were cropped to a size of 1024×1024, as only the palm region was of interest for the experiments. Due to extremely faded prints for a few palms, only 152 unique palms (1216 full palmprint images) were considered for the experiments reported here.

A total of 8 (2×4) partial palmprints were generated from the first two of the available full palmprint images of each palm, by cropping them each into four quarters. These partial palmprints were arbitrarily rotated and stored in a database, with a total of $152 \times 2 \times 4 = 1216$ samples. Figure 2 shows samples of full and partial palmprints available in the database used for testing purposes.

Two kinds of experiments were performed for this paper. In this first experiment, each partial palmprint (in some cases after being degraded) is compared with the two original full palmprints registered in the database. This experiment follows exactly the same strategy adopted in [12], replicating the same experimental setup. A total of 392,664 ($1216 \times 2 \times 152$) comparisons have been performed.

The second experiment, corresponds to a more realistic scenario, where partial palmprints are compared against the user's other six registered full palmprints, resulting in a total of 1,108,992 ($1216 \times 6 \times 152$) comparisons. Such experiments capture the intra-variability of different images of the same user, and were not considered in the paper proposing the original MPOC [12].
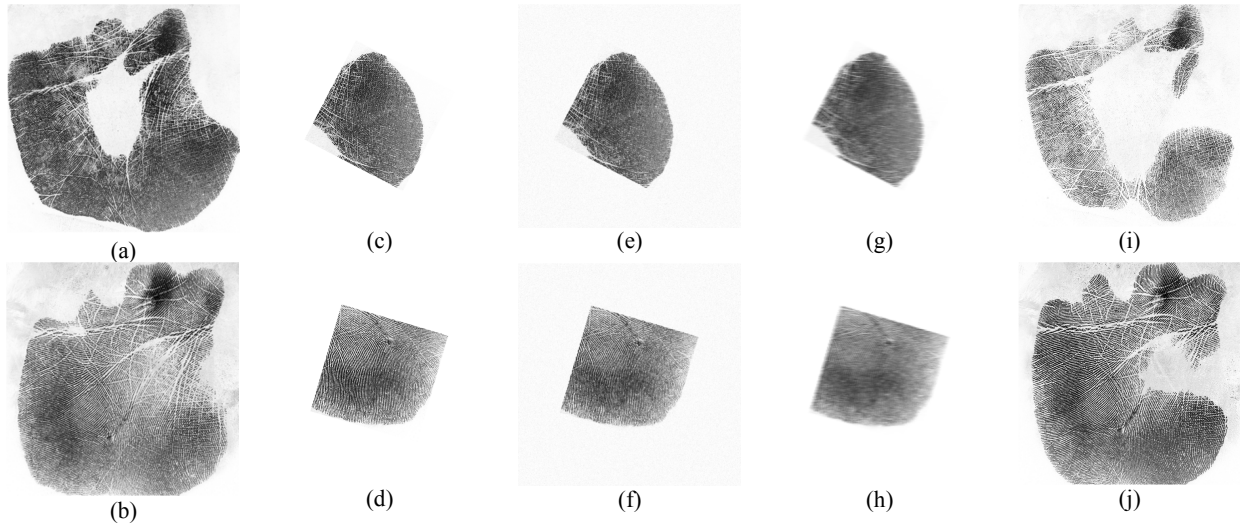
Figure 2: Full and partial palmprint samples: (a) and (b) – two full palmprint samples; (c) and (d) – randomly rotated partial palmprints samples; (e) and (f) – degraded by Gaussian noise; (g) and (h) – degraded by motion blur; and (i) and (j) different samples of (a) and (b), respectively.

For each experiment three types of tests were conducted: when no degradation (*test 1*), white additive Gaussian noise (*test 2*), or motion blur (*test 3*) are applied to the partial palmprints.

Gaussian noise and motion blur simulate the degradations that may be expected in real situations, e.g., due to dust particles accumulated over the palmprint, or due to smearing of the palm against a surface.

Gaussian noise with zero mean and 0.04 standard deviation was considered, while for motion blur a length of 22 pixels and zero degree angle were considered, since rotations with different angles were already considered. These parameter values are the same considered in [12], to make comparing results easier. Also, the same size of the MPOC *inside – lobe*, i.e. 11×11, is used.

Results are presented using the equal error rate values, EER, along with the decidability index, d', as proposed by Daugman [21].

The first comparison was made for a scenario using only *test 1* of experiment 1, to compare the original MPOC against the proposed PP-RIDER. From the results, included in Table 1, it can be seen that MPOC alone is not able to handle the partial palmprints when they are randomly rotated, while the proposed technique has shown its effectiveness in handling this situation, as shown by the very low EER and high d' values obtained.

The remaining recognition results are summarized in Table 2. Considering experiment 1, good results were achieved also when adding Gaussian noise to the partial palmprints (*test 2*), showing PP-RIDER's ability to handle well this type of image degradation. However, *test 3*, which involved degrading the randomly rotated partial palmprints with motion blur, has produced a poor result.

Table 1: Comparison of original MPOC with proposed PP-RIDER.

Experiment 1	Test 1 (no noise, no blur)	
	EER (%)	d'
MPOC	50.00	0.069
PP-RIDER	0.082	3.534

This indicates that the proposed technique is not very suitable for handling motion blur. In fact, a modification to the adopted MPOC algorithm used for comparisons may be required to better handle this type of degradation.

The performance of experiment 2 tests has degraded considerably in comparison to the experiment 1. This may be explained due to the fact that the MPOC technique is based on correlation and a lot of intra-user variability is observed in the different high resolution images of the same user, as shown in Figure 2 (a), (b), (i) and (j).

5. CONCLUSIONS

This paper proposes a novel rotation-invariant and degraded partial palmprint recognition method, PP-RIDER, which combines the merits of the FMT and MPOC techniques. For testing purposes, a partial palmprint database was generated by cropping the high resolution full palmprint images and then, these images were subjected to arbitrary rotations. Two kinds of experiments were performed: first, each partial palmprint was compared with the same full palmprint from which it was extracted; the second one performs comparisons against the remaining full

Table 2: Recognition results of all the experiments, with proposed technique PP-RIDER.

	Test1 (no noise, no blur)		Test2 (with noise, no blur)		Test3 (no noise, with blur)	
	EER (%)	$d^{'}$	EER (%)	$d^{'}$	EER (%)	$d^{'}$
Experiment 1	0.082	3.534	0.327	3.325	48.660	0.133
Experiment 2	31.916	0.890	32.440	0.894	49.820	0.036

palmprints of the same user.

Final results show a clear advantage of using PP-RIDER when compared to the original MPOC when dealing with arbitrarily rotated partial palmprints. Some limitations of the current PP-RIDER technique were also identified, notably in what concerns handling arbitrarily rotated partial palmprints degraded with motion blur, a big sensitivity to the intra-user variability observed in the high-resolution database images and also, sizes of both images need to be the same.

Future work will deal with the above mentioned limitations, for which the authors have already started some preliminary tests, which includes working on a feature-based alignment technique rather than correlation-based. This would provide more tolerance against small changes in the palmprint image details and also, exploit local rather than global information.

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