Partial Palmprint Matching for Forensic Applications

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ABSTRACT

Biometric identification based on palmprint trait has emerged as a powerful means for recognizing a person’s identity, being used in commercial and forensic applications. Most of the previous research is mainly focused on low-resolution, less than 100 pixels per inch (ppi), full-to-full palmprint recognition, with applications in access control. However, for forensic applications, high-resolution (500 ppi) palmprint images are required and partial-to-full palmprint matching must be supported. 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 complete high-resolution palmprint images into different regions/segments (called synthetic/ pseudo latent partial palmprints). Also, partial palmprint image matching is a challenging problem since these images may be arbitrarily rotated, incomplete and often noisy.

This thesis proposes two different kinds of novel approaches for partial-to-full palmprint matching: the first is known as PP-RIDER, which is based on Fourier Transform and the second is known as PP-RELIIF, which is based on local invariant features. For testing purposes, two databases: THUPALMLAB and PV-TEST-PARTIAL were used. The THUPALMLAB database contains only high-resolution full palmprint images; therefore, a novel partial palmprint database was generated by cropping the full palmprint images into different four regions/segments and then, subjected to arbitrarily rotations. On the other hand, the PV-TEST-PARTIAL database contains both high-resolution partial and full palmprint images. The results obtained are promising, especially when using the Fourier-based technique.

KEYWORDS

Biometric recognition, partial palmprint, full palmprint, forensics.
RESUMO

A identificação biométrica baseada em características da palma da mão tem-se vindo a afirmar como um método poderoso para a identificação e reconhecimento de pessoas, sendo usada tanto em aplicações comerciais como forenses. A maioria da investigação feita na área até agora tem-se focado essencialmente em imagens de baixa-resolução, menos de 100 pixels por polegada (ppi) e reconhecimento de imagens da palma da mão full-to-full, com aplicações em controlo de acessos. No entanto, para aplicações forenses, imagens de alta resolução (500 ppi) são necessárias assim como tem que ser suportado o reconhecimento de imagens partial-to-full. As imagens parciais são normalmente retiradas de superfícies (latent partial palmprints) ou podem ser igualmente geradas, para fins de testes, pelo recorte em diferentes regiões / segmentos de imagens completas de alta resolução (synthetic/ pseudo latent partial palmprints). O reconhecimento e matching de imagens da palma da mão parciais constitui um problema complexo devido à potencial origem das imagens, podendo estas estarem arbitrariamente rodadas, incompletas e por vezes com ruído.


Palavras-chave

Reconhecimento biométrico, palma da mão parcial, palma da mão completa, ciências forenses.
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List of Acronyms

$d'$ – Decidability Index

DFT – Discrete Fourier Transform

EER – Equal Error Rate

FAR – False Acceptance Rate

FRR – False Rejection Rate

FMT – Fourier-Mellin Transform

MPOC – Modified Phase-Only Correlation

POC – Phase-Only Correlation

PP-RIDER – Partial Palmprint Rotation-Invariant and DEgrated Recognition

PP-RELIF – Partial Palmprint REcognition using Local Invariant Features

PPI – Pixel per Inch

RANSAC – RANdom SAmples Consensus

ROC – Receiver Operating Characteristic

SIFT – Scale Invariant Feature Transform

SURF – Speeded Up Robust Feature
1. INTRODUCTION

1.1. CONTEXT AND MOTIVATION

Biometrics recognition is the science of identifying or verifying an individual’s identity based on his/her physical, physiological or behavioural characteristics [1]. Traditional recognition methods, such as knowledge-based (something that you know, e.g., password) and token-based (something that you have, e.g., personal identity number) are often unreliable, inconvenient, and/or inefficient, since they are not based on any inherent attributes of an individual. Therefore, they cannot differentiate between an authorized person (genuine user) and a person (impostor) who fraudulently possesses password or ID number of that authorized person [2]. Hence, by using biometrics it is possible to verify/identify an individual based on “who you are”, rather than by “what you possess” or “what you remember” [1]. Thus, biometric personal identification is a powerful means for automatically recognizing a person’s identity.

Current biometric recognition systems can use a variety of physical, physiological or behavioural characteristics, such as, fingerprint, palmprint, iris, signature, gait, ear, hand vein, face etc., to establish identity.

Palmprint as a biometric trait has received much attention in the last few years and has been considered as a good candidate for personal verification or identification, since it contains many useful and unique features [3], such as

(a) **Principal lines:** Both location and form of principal lines are unique which can be used for recognizing individuals, because they vary very little over time.

(b) **Wrinkles:** Wrinkles form rich texture in the hand and, are generally thinner and more irregular in comparison to principal lines.

(c) **Ridges:** Ridges are spread all over to the hand and are very thin; therefore need high resolution to see them.
(d) **Delta point:** Delta points are the center of delta-like region of the palmprint.

(e) **Minutiae point:** Minutiae points are the ridge characteristics, ridge ending and ridge bifurcation.

These important features can be observed at different image resolutions. For example, principal lines and wrinkles are observable in low-resolution palmprint images of less than 100 pixels per inch (ppi), while for ridges, delta point and minutiae point, high-resolution images of at least 400 ppi, are typically required [3]. Figure 1 shows an example of low-resolution and high-resolution palmprint images, along with all the above mentioned features.

Most of the researches conducted on the topic in the last few years are focused mainly on low-resolution (less than 150 ppi) full-to-full palmprint matching [4,5,6,7,8,9,10,11]. 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. This, in turn, makes it possible to develop real-time biometric recognition systems, which have recognition rates adequate for commercial purposes. However, for high-security applications (e.g., usages in forensic scenarios) high-resolution images (500 ppi, is a current standard resolution in forensic applications) are required, so that features like wrinkles and ridges can be visible; therefore, low-resolution palmprint systems are typically not suitable for forensic applications.

The most popular techniques for low-resolution full-to-full palmprint matching are:

(a) **Subspace-based methods:** Principal component analysis (PCA) [12], linear discriminant analysis (LDA) [13], or independent component analysis (ICA) [14].

(b) **Statistical-based methods:** Calculating moments, center of gravity or density from the whole palmprint images [15].

(c) **Transform-based methods:** Gabor transform [2], wavelet transform [16] or Fourier transform [17].

(d) **Coding-based methods:** Line orientation code [18], Competitive code [8] or Ordinal code [19].
In addition to high-resolution palmprint images, partial-to-full palmprint matching must also be supported [20]. Such partial palmprints could be either recovered from the palm impressions 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/degradations are added or not, respectively [20,21]. Figure 2 shows an example of pseudo, synthetic and real latent palmprints. It can be seen from the figure that pseudo latents have poorer quality than the synthetic latents.
Figure 2: An example of pseudo ((a) – (f)); synthetic ((g) – (l)) and real ((m) – (r)) latent palmprints, respectively. Real latent palmprints are taken from [20].
In fact, surveys conducted by law enforcement agencies show that 30% of the evidence recovered from the crime scenes are originated from palms, reinforcing the development of partial to full palmprint matching system [22]. Also, one of the goals of FBI’s Next Generation Identification (NGI) program is to develop a national palmprint identification system [23].
1.2. OBJECTIVE

Looking at the available literature [20,21,24,25,26], it can be seen that degraded partial palmprint matching is not a trivial task. Factors that make this problem difficult are described below:

- **Poor quality:** Partial palmprints generally are of poor quality due to the presence of noise/degradation (linear or non-linear) and illumination changes.

- **Incompleteness:** It is common that the palmprint evidences left at crime scenes are partial since very rarely full palmprints are obtained [25]. This makes conventional matching methods based on alignment (for example, minutiae matching), as used in fingerprint matching, to fail in partial palmprint matching problems.

- **Random rotation:** Generally, partial palmprints do not show well-defined structured shape (or contour shape) and often do not contain a reference point (for example, Delta point) that can be used for their alignment.

Figure 3 shows some examples of partial palmprint images and their corresponding full palmprints images.

Therefore, an objective of the thesis is to develop an automatically partial-to-full palmprint recognition technique, which should be able to handle random-rotation of the partial palmprint; robust against the acquisition noise and different types of degradations.
Figure 3: Sample full palmprints ((a), (f) and (k)) and Corresponding partial palmprints ((b) – (e), (g) – (j) and (l) – (o)), respectively.
1.3. CONTRIBUTIONS

The main contributions of this thesis are

- Proposal of two novel partial-to-full palmprint matching techniques:
  
  I. **Fourier-based partial-to-full palmprint recognition technique:** A rotation-invariant degraded partial palmprint matching technique, **PP-RIDER** (Partial Palmprint Rotation-Invariant and DEgraded Recognition). This technique uses the Fourier representation of the input images and combines the merits of Modified Phase-Only Correlation (MPOC) and Fourier-Mellin Transform (FMT) techniques. First, FMT is used to correct the random rotation of the partial palmprint image with respect to a registered full palmprint image and then, the concept behind the MPOC is used to calculate the similarity score between them.

  II. **Local Invariant Feature-based partial-to-full palmprint recognition technique:** This technique is also known as **PP-RELIF**, Partial Palmprint REcognition using Local Invariant Features. It is also rotation-invariant and targeted to degraded partial-to-full palmprint matching. This technique, first, calculates the invariant feature points (or interest points) by using Speeded-Up Robust Feature (SURF) technique, in both the input images. Then, these points are matched with each other to find out the common matches between them. Since, some of these matches may be inconsistent (called outliers) and are removed by using RANdom SAmple Consensus (RANSAC) algorithm, which outputs inliers. A novel way of matching is proposed which uses the spatial arrangements of these inliers in both the images.

- Further modification of the MPOC technique, for inclusion into the proposed PP-RIDER strategy. The original MPOC technique uses a fixed size of the *inside-lobe* which is $11 \times 11$. The *inside-lobe* is a square area in the correlation plane which contains a main peak at the middle. Several experiments were carried on
by using the different sizes of the inside-lobe, notably 61×61 and 101×101, showing the improvements of the results over the original size.

- Proposal of a new partial palmprint database. For the experimental results, a new partial palmprint database is generated from the THUPALMLAB high-resolution full palmprint database, called modified THUPALMLAB database. The partial palmprints are obtained by cropping from the full palmprints and being subjected to random-rotation and then, stored in the database. Several experiments are also performed when these images are degraded with either Gaussian noise or motion blur.

This thesis work has also contributed to a conference paper published in the 20th European Signal Processing Conference (EUSIPCO), Bucharest, Romania [27].
1.4. STRUCTURE OF THE THESIS

After this brief introductory chapter, the remainder of the dissertation is organized as follows:

- **Chapter 2 – REVIEW OF PARTIAL PALMPRINT RECOGNITION TECHNIQUES:** review shortly the papers published for partial palmprint recognition.
- **Chapter 3 – REVIEW OF RELEVANT IMAGE PROCESSING TECHNIQUES:** provides detail about some previously published image processing techniques that were further used for proposing the novel partial palmprint recognition techniques.
- **Chapter 4 – PROPOSED SOLUTION:** proposes two novel solutions for matching partial palmprints when they are randomly-rotated and/or degraded either with Gaussian noise or motion blur.
- **Chapter 5 – EXPERIMENTAL RESULTS:** discusses about the experimental results obtained from the proposed techniques.
- **Chapter 6 – CONCLUSIONS AND FUTURE WORKS:** draws conclusion and some suggestions about the future work.
2. REVIEW OF PARTIAL PALMPRINT RECOGNITION TECHNIQUES

Recently, partial palmprint matching is becoming an active topic of research and some work has been reported in this context, with Jain et al. [21], being the first to have published a technical report on latent palmprint matching, in 2008. A system that can match either a full or partial input image to a database of full palmprint images was developed. In that report, first a high-resolution full palmprint database was built by using a scanner and then, a partial palmprint database was created by cropping the full palmprint image into different regions (called sectors). There were a total of five partial palmprint images (five sectors) per full palmprint image. Furthermore, these partial palmprints were categorized into synthetic, if the quality of the images were high, i.e., no noise/degradation were added or pseudo, if the quality was poor, i.e., if degradations were added. Scale-Invariant Feature Transform (SIFT) and minutiae extraction techniques were applied for full to full and partial to full palmprint matching. Recognition rates of 95.6% and 82% were achieved for synthetic latent and pseudo latent palmprint databases, respectively.

Later in 2009, Laadjel et al. [24] presented a degraded (pseudo) partial palmprint database, which was built by cropping the full palmprint images into four regions (called quarters), each one covering an area of less than 25% of the original image. These partial palmprint images were intentionally degraded by adding Gaussian noise and motion blur. Laadjel et al. reported that recognition systems using SIFT and minutiae features presented some limitations: (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 [24] was then proposed and tested on a pseudo latent palmprint database. Partial palmprints were required to be in the same orientation as that of the original full palmprint. High recognition performance with Equal Error Rate (EER) of less than 0.4% was reported in
the paper. However, the comparisons were done with the partial palmprints against the full palmprints from which they were cropped.

Still in 2009, Jain et al. [20] proposed a new partial-to-full palmprint matching algorithm which was based on minutiae matching, called MinutiaeCode. Also, a novel palmprint enhancement technique was reported in the paper, which takes more account about the characteristics of palmprints. This technique was needed since the performance of a minutiae extraction algorithm depends heavily on the quality of the input image. The proposed minutiae matching algorithm, MinutiaeCode, was tested on two sets of partial palmprint databases: live-scan (synthetic) partial palmprint and latent (real) partial palmprints. The first set was collected using a scanner while the second one was provided by Noblis and the forensic science division of Michigan state police (MSP). Recognition rates of 78.7% and 69%, were achieved for live-scan and latent partial palmprint databases, respectively. 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, Laaddjel et al. [25] presented a new rotation invariant technique in which the palmprint images were first enhanced by using a conventional fingerprint enhancement technique [28], followed by calculating an invariant feature descriptor around each minutiae, which is referred to as Invariant Local Minutiae Descriptor (ILMD). Their method computes the gradient magnitude and orientation at each sample point within a local region of size $16 \times 16$ around each minutia and finally, a set of orientation histograms is formed. This allows for the descriptors to be rotation invariant and do not need any image alignment before the matching stage. High recognition rate with an EER of less than 0.8% was obtained.

Recently, in 2011, Dai et al. [29] presented a first large-scale publicly available high-resolution palmprint database, which is referred to as THUPALMLAB. Multiple features, such as, minutiae, density, orientation and principal lines, were used for palmprint recognition in [29] and the density map feature was reported to perform the best among them. However, the main focus of the research was on full-to-full
palmprint matching, although experimental results on partial-to-full palmprint were also reported. Recognition rate of 91.7% was achieved in the case of partial-to-full palmprint matching.

Still in the same year, 2011, Wang et al. [26] used 22 latent palmprints from real forensic cases and 8680 full palmprints from the criminal investigation field captured by Beijing Institute of Criminal Technology in China for performance evaluation. A radial triangulation method has been used for minutiae modelling in case of partial-to-full palmprint matching, which was originally developed for fingerprint recognition. This method exploits the spatial arrangement of minutiae, which can be modelled through a triangulation of a polygon whose vertices represents the minutiae locations. Recognition rate of 62% was reported in the paper.
3. REVIEW OF RELEVANT IMAGE PROCESSING TECHNIQUES

In this chapter, existing state-of-the art image processing techniques are described in detail. These techniques are then further used for the proposed techniques.

Orders of using these techniques are: Sections 3.1 and 3.2 describe the techniques which are later used for proposing the first technique (described in Section 4.1) and Sections 3.3 and 3.4 describe the techniques which are later used for proposing the last technique (described in Section 4.2).

3.1. MODIFIED PHASE-ONLY CORRELATION

Motivations behind using Modified Phase-Only Correlation (MPOC) for the partial-to-full palmprint matching are: (i) simplicity; (ii) fast computation; and (iii) a high recognition rate for partial-to-full palmprint matching, as mentioned in the original paper [24].

The MPOC technique is the modified version of the original Phase-Only Correlation (POC) [30]. POC is a correlation-based technique which has been successfully applied in different biometric recognition applications, for instance, palmprint [31], fingerprint [32] or iris [33]. It exploits the phase component of an image’s Fourier Transform, as it has been shown to contain more information than the amplitude component for this application [24]. 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 \( M \times N \). Then, their 2D Discrete Fourier Transforms (2D DFTs), along with the polar form, can be written as
\[ F(u, v) = \frac{1}{M \times N} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) e^{-j2\pi(xu/M+yu/N)} \]
\[ = \text{Mag}_1(u, v) e^{j\Theta_1(u, v)}, \]

\[ G(u, v) = \frac{1}{M \times N} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} g(x, y) e^{-j2\pi(xu/M+yu/N)} \]
\[ = \text{Mag}_2(u, v) e^{j\Theta_2(u, v)}, \]

where \( u = 0, 1...M-1 \) and \( v = 0, 1...N-1 \). \( \text{Mag}_1(u, v) \) and \( \text{Mag}_2(u, v) \) are the magnitudes (or amplitudes), and \( \Theta_1(u, v) \) and \( \Theta_2(u, v) \) are the phase components of the Fourier Transform of both the images, respectively.

The normalized cross-power spectrum, \( P_{f,g}(u, v) \), between these two images can be defined as

\[ P_{f,g}(u, v) = \frac{F(u, v) \times G^*(u, v)}{|F(u, v) \times G^*(u, v)|} e^{j(\Theta_1(u, v) - \Theta_2(u, v))}, \]

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

The POC function \([30]\), \( \text{poc}_{f,g}(x, y) \) is the 2D Inverse Discrete Fourier Transform (2D IDFT) of \( P_{f,g}(u, v) \) and is given by

\[ \text{poc}_{f,g}(x, y) = \text{FT}^{-1}\left( P_{f,g}(u, v) \right) \]
\[ = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} P_{f,g}(u, v) e^{j2\pi(xu/M+yu/N)}, \]

This produces a sharp peak at the center of the correlation plane when performing a genuine user matching attempt, while the peaks drop significantly for the impostor matching.

Figure 4 illustrates the stepwise calculation of the POC function between a full image and a partial image.
POC presents a number of important properties, like translation and brightness invariance or immunity against the noise, as described in the following subsections.

3.1.1. TRANSLATION INVARIANCE

Let \( g_1(x, y) \) be a translated version of the original image \( g(x, y) \), which can be written as

\[
g_1(x, y) = g(x - x_0, y - y_0),
\]

where \((x_0, y_0)\) is the displacement vector. The relationship between the Fourier Transforms of \( g_1(x, y) \) and \( g(x, y) \): \( G_1(u, v) \) and \( G(u, v) \), respectively, can be written as

\[
G_1(u, v) = e^{-2\pi i (ux_0/M + vy_0/N)} G(u, v),
\]

Therefore, the POC function between the images \( f(x, y) \) and \( g(x, y) \) can be written as

\[
poc_{f, g_1}(x, y) = FT^{-1} \left( e^{-2\pi i (ux_0/M + vy_0/N)} e^{i\theta(u, v) - \theta_0(u, v)} \right) = poc_{f, g}(x - x_0, y - y_0).
\]
Hence, a translation results in a correlation peak shift by \((x_0, y_0)\), and POC can thus be considered invariant to image translation.

### 3.1.2. BRIGHTNESS INVARIANCE

Let \(g_2(x, y)\) be a brightness-scaled version of the original \(g(x, y)\) image, with the relationship between them being

\[
g_2(x, y) = \alpha g(x, y),
\]

where \(\alpha > 0\) is a brightness scaling factor.

The Fourier Transform of \(g_2(x, y)\), \(G_2(u, v)\), is then given by

\[
G_2(u, v) = \alpha G(u, v),
\]

The POC function between \(f(x, y)\) and \(g_2(x, y)\) is given by

\[
poc_{f,g_2}(x, y) = poc_{f,g}(x, y).
\]

The above equation shows that the POC is not influenced by the uniform brightness changes.

### 3.1.3. NOISE IMMUNITY

Figure 5 (i) and (j) shows the POC function when white additive Gaussian noise of zero mean and standard deviation of 0.04, is added to a partial palmprint of the same user. It can be clearly seen that the height of the peak decreases, when Figure 5 (e) and (f) are compared, but without changing its shape, thus, shows that POC has a strong immunity against Gaussian noise.

Laadjel et al. [24] further modified this technique to make it even more robust against the noise, by proposing MPOC technique. A new peak measurement value, \(mpoc_{f,g}\), is introduced as the ratio between the highest peak in an area of size \(11 \times 11\), the inside-
lobe centered at the highest peak and the highest peak value in the remaining area of the correlation plane, the outside-lobe expressed as

\[
mpoc_{f,g} = \frac{\arg \max \left( \text{inside-lobe} \left( poc_{f,g}(x,y) \right) \right)}{\arg \max \left( \text{outside-lobe} \left( poc_{f,g}(x,y) \right) \right)}. \tag{11}
\]

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 5 (a), (b), (e) and (f). Otherwise, the height of the main peak, as well as the mpoc value, drops significantly, as illustrated Figure 5 (a), (c), (g) and (h). In addition, Figure 5 (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.
Figure 5: 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.

3.2. FOURIER-MELLIN TRANSFORM

FMT [34,35] is an image registration technique which matches images that are translated, rotated and scaled with respect to one another in the Fourier domain. The first proposed technique (described in Section 4.1) explores only the rotation property of the FMT allowing the alignment of randomly rotated images. Scaling factor is assumed to be constant among the partial and full palmprint images, therefore, scaling property of the FMT is not considered.

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 $\theta_0$, then $f_2(x, y)$ can be written as

$$f_2(x, y) = f_1(x \cos \theta_0 + y \sin \theta_0 - x_0, -x \sin \theta_0 + y \cos \theta_0 - y_0).$$

(12)

According to the Fourier translation and rotation properties, the Fourier Transforms of $f_1(x, y)$ and $f_2(x, y)$ can be related as

$$F_2(u, v) = e^{-j2\pi(uu_0 + vv_0)} F_1(u \cos \theta_0 + v \sin \theta_0, -u \sin \theta_0 + v \cos \theta_0).$$

(13)

Let $Mag_1$ and $Mag_2$ be the magnitudes of $F_1(u, v)$ and $F_2(u, v)$, which can written as

$$Mag_2(u, v) = Mag_1(u \cos \theta_0 + v \sin \theta_0, -u \sin \theta_0 + v \cos \theta_0).$$

(14)

It can be seen from the above equation that the magnitudes of both spectra are same but one is a rotated replica of other. The above equation can be written in polar or log-polar coordinates as

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

(15)

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

(16)
The proposed technique uses equation (16) for computing the rotation angle \( \theta_0 \), by using phase correlation. For more details about the FMT implementation can be formed in [35].

3.3. SPEEDED-UP ROBUST FEATURES

Two of the most important approaches published in the literature for finding salient features in an image are: Scale-Invariant Feature Transform (SIFT), proposed by Lowe et al. [36] in 2004, and Speeded-Up Robust Features (SURF), proposed by Bay et al. [37] in 2008. Both of these approaches do not only detect interest points but also create an invariant descriptor for each of them. Although, SIFT and SURF share many common properties and in some conditions may perform almost the same, SURF has been chosen for this thesis work because of its faster computation over the SIFT [37].

The major steps to detect the set of SURF features in the image are shortly described below.

3.3.1. INTEREST POINT DETECTION

The SURF technique uses integral images (see equation (17)) which reduce the computation time drastically. These integral images allow for fast computation of box type convolution filters. The integral image \( I_{\Sigma}(x, y) \) is given by

\[
I_{\Sigma}(x, y) = \sum_{i=0}^{\lfloor x \rfloor} \sum_{j=0}^{\lfloor y \rfloor} I(i, j),
\]

(17)

where \( I \) represents an input image.

The Hessian matrix is used as an interest point detector by the SURF technique, due to its good performance in accuracy and time. Given a point \((x, y)\) in an image \( I \), the Hessian matrix \( H(x, y, \sigma) \) in \((x, y)\) at scale \( \sigma \) is given by:
\[ H(x, y, \sigma) = \begin{bmatrix} L_{xx}(x, y, \sigma) & L_{xy}(x, y, \sigma) \\ L_{xy}(x, y, \sigma) & L_{yy}(x, y, \sigma) \end{bmatrix} \]

where \( L_{xx}(x, y, \sigma) \) is the convolution of Gaussian second order derivative \( \frac{\partial^2}{\partial x^2} g(\sigma) \) with the image \( I \) in point \( (x, y) \), and similarly for \( L_{xy}(x, y, \sigma) \) and \( L_{yy}(x, y, \sigma) \). The interest points are found at locations where the determinant of the Hessian matrix is maximum.

Gaussians are optimal for scale-space analysis but in practice they have to be discretised and cropped. Bay et al. [37] used box filters to approximate the second order Gaussian derivatives. These approximations can be evaluated at a very low computation cost using the integral images. Figure 6 shows the approximation of second order Gaussian derivatives by box filters.

![Approximation of second order Gaussian derivatives by box filters](image)

**Figure 6:** Approximation of second order Gaussian derivatives by box filters. Image adapted from [37].

For the matching process to be scale invariant, interest points need to be found at different scales. Scale spaces are usually represented as an image pyramid. Due to the use of box filters and integral images, the box filters of any size can be applied on the original image exactly at the same speed of image pyramids. Therefore, the scale space is analysed by up-scaling the filter size rather than iteratively reducing the image size.

Finally, to localise the interest points in the image and over different scales, non-maximum suppression in a \( 3 \times 3 \times 3 \) neighbourhood is applied.
3.3.2. INTEREST POINT DESCRIPTION

After the detection of interest points, their descriptors are defined which describe the distribution of intensity content within the interest point neighbourhood, similar to the gradient information extracted by SIFT [36]. Steps for calculating these descriptors include: First, calculation of a reproducible orientation based on information from a circular region around the interest point and then, constructing a square region and extracting the SURF descriptor from it.

A reproducible orientation needs to be found for the interest point, in order to be rotation invariant. For this purposes, Haar wavelet responses in $x$ and $y$ directions have been calculated within a circular neighbourhood of radius of $6s$ around the interest point, with $s$ being the scale at which the interest point was detected. Figure 7 shows the Haar wavelets and the orientation assignment.

![Haar wavelets](image)

Figure 7: (a) – Haar wavelets to compute responses along x and y directions and (b) – Orientation assignment. Image adapted from [37].

For the extraction of the descriptor, a square region centered, of size $20s$, at the interest point is constructed along the direction calculated at the previous step. The region is split-up regularly into smaller $4 \times 4$ square sub-regions. Haar wavelet responses along the horizontal and vertical directions, $d_x$ and $d_y$, are calculated. These responses are then summed up over each sub-region and form a first set of entries in the feature vector. In order to bring information about the polarity of the intensity
changes, the sum of the absolute values of the responses, $|d_x|$ and $|d_y|$, are also extracted. Hence, each sub-region has a four-dimensional descriptor vector $v$,

$$v = (\sum d_x, \sum d_y, \sum |d_x|, \sum |d_y|).$$

(19)

Figure 8 shows the descriptor entries of a sub-region under three different conditions. Left: in case of a homogenous region all the values are low; Middle: in the presence of frequencies in $x$ direction, the value of $\sum |d_x|$ is high, but others are low and Right: if the intensity is gradually increasing in $x$ direction, both the values $\sum d_x$ and $\sum |d_x|$ are high.

![Figure 8: Descriptor entries under three different conditions. Image adapted from [37].](image)

### 3.4. RANDOM SAMPLE CONSENSUS

RANdom SAmple Consensus (RANSAC) is an iterative method to estimate parameters of a mathematical model from a set of observed data which contains outliers [38]. A basic assumption is that the data consists of “inliers”, i.e., data whose distribution can be explained by some set of model parameters, and “outliers” which are the data that do not fit the model.

In this thesis work, affine transformation (rotation and translation) model has been estimated by using the RANSAC, given the set of matching points/correspondences between the two images. Also, there is no scaling related between the partial and full palmprints in the current databases.

A simple example is fitting a 2D line to a set of observations. Assuming the set of observations (or the input data) contains both inliers, i.e., points which approximately
can be fitted to a line and outliers, points which cannot be fitted to this line. A simple least squares method for line fitting will in general produce a line with a bad fit to the inliers. This is because the method tries to fit it optimally among all the points, including the outliers. RANSAC, on the other hand, can produce a model which is only computed from the inliers provided the number of inliers in the observed data is sufficiently high.

Figure 9 shows the example of fitting a line using RANSAC to a set of observations that contain both inliers and outliers.

Figure 9: (a) – a set of observations with many outliers and a line needs to be fitted in this data and (b) – line fitting with RANSAC. Image adapted from [39].
4. PROPOSED SOLUTION

Two novel techniques for partial-to-full palmprint matching are proposed in this thesis, which are different in nature, i.e. the first technique exploits the Fourier representation of the input images and uses the correlation for finding the similarity score between the images while the second technique uses the local invariant features for the matching between the two images.

4.1. FOURIER-BASED PARTIAL PALMPRINT RECOGNITION TECHNIQUE

A novel rotation-invariant degraded partial palmprint matching technique, known as Partial Palmprint Rotation-Invariant and DEgraded Recognition, PP-RIDER, is proposed in this work, which is based on Fourier representation of the images and combines Modified Phase-Only Correlation (MPOC) technique [24] with Fourier-Mellin Transform (FMT) technique [34,35]. PP-RIDER aims at further improving the MPOC performance, notably in the presence of arbitrary rotations.

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 the matching purposes, applying it to the aligned images.

The overall system architecture of the proposed technique is shown in Figure 10.
Figure 10: System architecture of PP-RIDER technique.

4.1.1. DIFFERENT SIZES OF INSIDE-LOBE IN MPOC TECHNIQUE

Laadjel et al. [24] explained the reason behind using the maximum peak in outside-lobe of the correlation plane was to increase the reliability of the peak discrimination. Those authors further explained that the outside-lobe of the correlation plane maintains either flat, approximately flat and spurious peaks under different scenarios, which can occurs when: (i) same user’s partial and full palmprint images; (ii) same user’s noisy partial and clean full palmprint images and (iii) different partial and full palmprint images are matched, respectively.

However, it has been found that in any of the above mentioned cases, there are always some distributions of spurious peaks around the main peak (see Figure 11). Some of those spurious peaks have approximately the same height as that of main peak and if any of them belong to the outside-lobe would affect the new peak value \( m_{mpoc}^{f,g} \), since this value is the ratio of the maximum values in inside-lobe and outside-lobe of the correlation plane. For example, if the size of the inside-lobe is small might means the division of two significant same values and would eventually results in a lower similarity score, thus affecting the final recognition rate.

This could be better explained by looking into the correlation and measure how wide is the distribution of the peaks, thus, a better size for the inside-lobe would be that
includes all those spurious peaks around the main peak. For example, from Figure 11(a) and (b), and thereby same for the rest (c) and (d) and (e) and (f), it can be seen that the width (in pixels) of the distribution is 25, hence, if the inside-lobe of size $11 \times 11$ is used, then it gives a new peak value of 1.44 and 1.04 in genuine and impostor matches, respectively. However, if the size $61 \times 61$ is used, the values 7.27 and 1.04 are obtained in both matches. In the first case, the values were close to each other while in the second case they are discriminative; hence, this shows that the size selected for the inside-lobe can have a direct impact on the final recognition rate.
Figure 11: Different correlation planes showing spurious peaks around the main peak: (a), (c) and (e) – Showing correlation planes and (b), (d) and (f) – Corresponding correlation planes but in a zoomed top view.

In this thesis work, after some preliminary experiments, three different sizes (11×11, 61×61 and 101×101) of the inside-lobe for MPOC technique have been chosen for all the experiments to explore their effects on the final results.
4.2. LOCAL INVARIANT FEATURES-BASED PARTIAL PALMPRINT RECOGNITION TECHNIQUE

Another novel local feature-based technique, rather than Fourier-based, is proposed in this thesis, also known as PP-RELIF (Partial Palmprint REcognition using Local Invariant Features). Figure 12 shows the overall system architecture of the proposed technique. In the proposed technique, first, local invariant interest points (also called feature points/ keypoints) are detected in both the input images and then, a descriptor vector is computed for each of them. This descriptor is highly distinctive and partially invariant to variations such as illumination, rotation, scale and 3D viewpoint. These interest points and their corresponding descriptor vectors are computed by using the well-known SURF technique [37].

In the feature matching stage, the descriptors from both the images are matched with each other to find out the matches between them. After the feature matching, there is a possibility of inconsistent matches (i.e., outliers) and therefore, they should be removed from the set. For this purpose, another well-known and robust algorithm, RANSAC [38], has been chosen and applied to remove the set of outliers from the matching set. A set of inliers is obtained as an output after applying the RANSAC algorithm. Finally, spatial arrangements of these inliers in both the images are used for the matching process. A further detail about it is given in the following sub-section.

4.2.1. ERROR MEASURE FOR THE MATCHING PROCESS

After the inliers obtained from both the input images, for the matching process, a novel error measure is proposed which exploits the spatial arrangement of these inliers (i.e., local keypoint structures) in both images. It should be noted that this error measure is only valid when there is no scaling between the images, which is true in the present case.

This measure is calculated as follows: first, the Euclidean distances are computed separately for each pair of the inliers in both the images. These distances do not
depend on the direction in which they are calculated but same order is always kept when calculating them, because the correspondences between each of the inliers in both the image are known, to avoid any kind of mismatch during the calculation of an error measure.

For example, let $t$ and $r$ represent the test partial palmprint and registered full palmprint images, and also suppose that after the RANSAC algorithm, $n$ be the number of inliers found in both the images. Therefore, two set of distances are
obtained, which can be represented by \( D = \{d_1', d_2', d_3', \ldots, d_n'\} \) and \( D' = \{d_1, d_2, d_3, \ldots, d_n\} \), for each of the images, respectively.

Then, each of these set of distances can be written as

\[
d_i' = \sqrt{(y_{i+1}' - y_i')^2 + (x_{i+1}' - x_i')^2} \quad \text{and},
\]
\[
d_j' = \sqrt{(y_{j+1}' - y_j')^2 + (x_{j+1}' - x_j')^2}
\]

where, \((x', y')\) and \((x', y')\) are the coordinates of the interest point in test partial palmprint image and registered full palmprint image, respectively.

Since, the correspondences between each of the inliers in both the images are known and also, the same order for calculating the above distances are kept, therefore, the error measure between the images can be formulated as

\[
e^{tr} = \frac{1}{n} \sum_{i=1}^{n} (d_i' - d_i')^2.
\]

Hence, the proposed error measure \( e^{tr} \) measures how much the spatial arrangement of the inliers in both the images differs with each other. Therefore, one can expect a low value of it when both the input images are from the same user, otherwise it should be high.

Figure 13 and Figure 14 show all the steps of this proposed technique for a genuine and an impostor cases, respectively. For example, Figure 13 (a) and (b) represent two input full palmprint and partial palmprint images for the genuine case, respectively. Then, SURF interest points are calculated for both the images and are matched with each other, as shown in Figure 13 (c) – (e). Since, it can be possible that from this set of matched points, there exist some inconsistent matches which are called outliers. Hence, it is important to remove them before any matching procedure. To remove the outliers from both the images, RANSAC algorithm is applied, which outputs inliers. Figure 13 (f) shows the inliers in both the images and their correspondences in both the images. Figure 13 (g) – (j) again shows the same inliers in both the images but in a
zoomed view, so that their spatial arrangements (or structures) can be seen. Finally, Figure 13 (k) and (l) show the set of distances computed for each of the images and these, distances are later used for calculated the error measure between them. Similar steps are also performed for the impostor case, shown in Figure 14.
Figure 13: Various steps in the proposed technique in case of a genuine match: (a) and (b) – full and partial palmprints from the same user; (c) and (d) – calculating SURF interest points in both the images; (e) – matching the interest points between them; (f) – inliers after RANSAC; (g), (h), (i) and (j) – inliers in full and partial palmprints and (k) and (l) – exploiting spatial arrangement of inliers in both the images.
Figure 14: Various steps of the proposed technique in case of an impostor match: (a) and (b) – full and partial palmprints from different users; (c) and (d) – calculating SURF keypoints in both the images; (e) – matching the keypoints between them; (f) – inliers after RANSAC; (g), (h), (i) and (j) – inliers in full and partial palmprints and (k) and (l) – exploiting spatial arrangement of inliers in both the images.
5. EXPERIMENTAL RESULTS

The proposed partial palmprint recognition techniques have been tested using two databases: a modified version of THUPALMLAB [40] and PV-TEST-PARTIAL [41]. The databases used for the performance evaluation are summarized in Table 1.

Table 1: Databases’ specifications used for experimental testing.

<table>
<thead>
<tr>
<th></th>
<th>Original THUPALMLAB database</th>
<th>PV-TEST-PARTIAL database</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of palms (or users)</td>
<td>160</td>
<td>10</td>
</tr>
<tr>
<td>Number of full palmprint images per palm</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td>Total number of full palmprint images</td>
<td>1280</td>
<td>80</td>
</tr>
<tr>
<td>Number of partial palmprint images per palm</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>Total number of partial palmprint images</td>
<td>0</td>
<td>40</td>
</tr>
<tr>
<td>Original size of full palmprints</td>
<td>2040x2040</td>
<td>2500x2552</td>
</tr>
<tr>
<td>Resolution (in ppi)</td>
<td>500</td>
<td>500</td>
</tr>
<tr>
<td>Arbitrary rotation</td>
<td>0 to 360 degrees</td>
<td>0 to 90 degrees</td>
</tr>
<tr>
<td>Acquisition method</td>
<td>Hisign scanner</td>
<td>Cogent FTIR scanner</td>
</tr>
</tbody>
</table>

The images in THUPALMLAB database were cropped to a size of 1024×1024, as only the palm region was of interest for the experiments. Due to extremely faded prints of a few palms, only 152 unique palms (1216 full palmprint images) were considered for the experiments reported here.

A new partial palmprint database has been created from the THUPALMLAB database, since it does not contains partial palmprint images. 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 into four different quarters. These partial palmprints were randomly rotated and stored in a database, with a total of 152×2×4 = 1216 samples. Later on, all these partial palmprint images are merged together with the full
palmprint images of THUPALMLAB database into a new database, called as modified THUPALMLAB.

Figure 15 and Figure 16 show some samples of full palmprints and corresponding partial palmprints, as well subjected to degradations caused by Gaussian noise and motion blur for the modified THUPALMLAB and PV-TEST-PARTIAL databases, respectively.
Figure 15: Full and partial palmprint samples from modified THUPALMLAB database: (a), (b) and (c) – three full palmprint samples; (d), (e) and (f) – randomly rotated partial palmprints; (g), (h) and (i) – degraded by Gaussian noise and (j), (k) and (l) – degraded by motion blur.
Figure 16: Full and partial palmprint samples from PV-TEST-PARTIAL database: (a), (b) and (c) – three full palmprint samples; (d), (e) and (f) – corresponding partial palmprint samples; (g), (h) and (i) – degraded by Gaussian noise and (j), (k) and (l) – degraded by motion blur.
Figure 17 and Figure 18 show the intra-variability of the full palmprints for the same user, as observed in both databases. These intra-variabilities include intensity difference, missing of some parts of palm, presence of random noise and arbitrarily rotated.

Figure 17: Example of intra-variability within the full palmprint images of the user of THUPALMLAB database. Each row corresponds to a different user.
Figure 18: Example of intra-variability within the full palmprint images of the user of PV-TEST-PARTIAL database. Each row corresponds to a different user.

Due to time-constraints, the PP-RELIF technique is applied only to PV-TEST-PARTIAL database because of its smaller size. Also, each partial palmprint of the PV-TEST-PARTIAL database is compared only with the second full palmprint image (out of eight) of each user in the database, to fasten the comparisons. Second full palmprint image is chosen since it is the most complete, among all the eight full prints [41].
Four different kinds of experiments were performed in this thesis work, which are described as follows:

(a) **Experiment 1:** For the purpose of allowing a comparison between the original MPOC and the proposed PP-RIDER techniques, the modified THUPALMLAB database has been used in this experiment. No degradations, i.e., no Gaussian noise or motion blur were applied to the partial palmprints and also, the same size of the *inside-lobe* i.e. $11 \times 11$, were used. Each partial palmprint is compared with the first two original full palmprints from which they were extracted. This experiment follows exactly the same strategy adopted in [24], replicating the original experimental setup. A total of $392,664$ ($1216 \times 2 \times 152$) comparisons have been performed.

(b) **Experiment 2:** This and all the remaining experiments, correspond to a more realistic scenario, where partial palmprints were compared against the user’s other registered full palmprints. PP-RIDER was tested using both databases, considering six and eight registered full palmprints, for the modified THUPALMLAB and PV-TEST-PARTIAL databases, respectively. Whereas, PP-RELIF technique compares the partial palmprints only with the second registered full palmprint of the PV-TEST-PARTIAL database. All these details are summarized in Table 2.

Such experiments capture the intra-variability of different images of the same user, and were not
considered in the original MPOC paper.

In this experiment, no degradations were applied to the partial palmprint images.

(c) **Experiment 3**: In this experiment, partial palmprints were degraded with white additive Gaussian noise but without blurring them.

(d) **Experiment 4**: Partial palmprints were degraded with motion blur but without applying the Gaussian noise.

Table 2 summarizes all the details about the Intra- and Inter-class comparisons of the proposed techniques for experiments 2, 3 and 4.

<table>
<thead>
<tr>
<th></th>
<th>PP-RIDER technique</th>
<th></th>
<th>PP-RELIF technique</th>
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<tbody>
<tr>
<td></td>
<td>(Databases used)</td>
<td></td>
<td>(Database used)</td>
</tr>
<tr>
<td>Modified THUPALMLAB</td>
<td>PP-TEST-PARTIAL</td>
<td>PV-TEST-PARTIAL</td>
<td></td>
</tr>
<tr>
<td>Number of registered</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>full palmprints</td>
<td>6</td>
<td>8</td>
<td>1</td>
</tr>
<tr>
<td>Number of test partial palmprints</td>
<td>8</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Total number of comparisons</td>
<td>1,108,992</td>
<td>3,200</td>
<td>400</td>
</tr>
<tr>
<td>Intra-class comparisons</td>
<td>7,296</td>
<td>320</td>
<td>40</td>
</tr>
<tr>
<td>Inter-class comparisons</td>
<td>1,101,696</td>
<td>2,880</td>
<td>360</td>
</tr>
</tbody>
</table>

Gaussian noise and motion blur simulate degradations that may be expected to be encountered in the 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 for the partial palmprint images. Theses parameter values are the same considered in [24], to make comparing results easier.

Results are presented by using the Equal Error Rate (EER) values, along with the decidability index, $d'$, as proposed by Daugman [42].

EER is defined as a point in the Receiver Operating Characteristics (ROC) curve where the False Acceptance Rate (FAR) equals to the False Reject Rate (FRR). Whereas, FAR is the probability of a successful attempt by an impostor and FRR is the probability of a failed access attempt by a genuine user. Figure 19 (a) and (b) show the genuine and impostor distributions, and the ROC curve.

The $d'$-prime value measures the separation between the means of the genuine and impostor distribution probability distributions. If $\mu_1$, $\mu_2$ , $\sigma_1$, and $\sigma_2$ are the means and standard deviation of genuine and impostor distributions, respectively, then $d'$ is defined as,

$$d' = \frac{\mu_1 - \mu_2}{\sqrt{\frac{\sigma_1^2 + \sigma_2^2}{2}}}$$  \hspace{1cm} (22)
Figure 19: (a) – Genuine and impostor distributions showing False Acceptance Rate (FAR), False Reject Rate (FRR) and Threshold (T) and (b) – Receiver Operating Characteristics (ROC) curve showing Equal Error Rate (ERR). This image is taken from [1].

Following sub-sections describe each of the experiments performed.

5.1. EXPERIMENT1: Comparison between MPOC and PP-RIDER

This experiment compares the original MPOC and the proposed PP-RIDER. Sizes of the inside-lobe used in both of the techniques are kept as in the original MPOC proposal, i.e., 11×11 and also, the same strategy for the comparison between the partial and full palmprints is used. Table 3 shows the recognition performance of both the techniques.

Table 3: Comparison of original MPOC with the proposed PP-RIDER using modified THUPALMLAB database.

<table>
<thead>
<tr>
<th>Experiment 1: No noise and no blur (modified THUPALMLAB)</th>
<th>MPOC (size: 11×11)</th>
<th>PP-RIDER (size: 11×11)</th>
</tr>
</thead>
<tbody>
<tr>
<td>EER (%)</td>
<td>50.00</td>
<td>0.082</td>
</tr>
<tr>
<td>d'</td>
<td>0.069</td>
<td>3.534</td>
</tr>
</tbody>
</table>
From the results presented above, 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.

For the remaining experiments, following things are performed: (i) different sizes of inside-lobe of the PP-RIDER have been explored and their results are compared; (ii) use of both partial palmprint databases and (iii) experimental results with both proposed techniques: PP-RIDER and PP-RELIF.

5.2. EXPERIMENT2: Partial palmprints without noise and blur

In this and the following experiments a more realistic scenario, where a partial palmprint is compared a previously (different) full palmprint enrolled in the database is considered. In this experiment, partial palmprints are not degraded either with Gaussian noise or with motion blur.

Three different sizes of the inside-lobe are considered for the PP-RIDER technique and the corresponding recognition results for both the databases are presented in Table 4 and Table 5. For the PP-RELIF technique, results are evaluated using the PV-TEST-PARTIAL database and presented in Table 5.

Table 4: Recognition results of PP-RIDER without any degradation for modified THUPALMLAB database.

<table>
<thead>
<tr>
<th>Experiment2: No noise and no blur (modified THUPALMLAB)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>PP-RIDER (size: 11x11)</td>
<td>PP-RIDER (size: 61x61)</td>
<td>PP-RIDER (size: 101x101)</td>
</tr>
<tr>
<td>EER (%)</td>
<td>31.916</td>
<td>27.305</td>
</tr>
<tr>
<td>$d'$</td>
<td>0.8900</td>
<td>0.9241</td>
</tr>
</tbody>
</table>
Table 5: Recognition results of both the techniques using PV-TEST-PARTIAL database.

<table>
<thead>
<tr>
<th>Experiment 2: No noise and no blur (PV-TEST-PARTIAL)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PP-RIDER</strong> (size: 11×11)</td>
</tr>
<tr>
<td>EER (%)</td>
</tr>
<tr>
<td>(d')</td>
</tr>
</tbody>
</table>

From Table 4 and Table 5, it is clear that the size of the inside-lobe plays an important role in the recognition performance of PP-RIDER technique because, as the size increases, the EER and \(d'\) values gradually decrease and increase, respectively. In both the cases, largest sizes, i.e. 101×101 has achieved the lowest EERs. It can be noted that although these results are poorer when compared to full-to-full palmprint matching, however, a similar reduction in performance are observed in the available literature [20,29] and also, in other similar biometric system, for example, partial fingerprint matching [44].

For the PP-RELIF technique, higher EER and lower \(d'\) values are achieved in comparison with the PP-RIDER, for the PV-TEST-PARTIAL database shown in Table 5. This may be justified by the fact that in the PP-RELIF technique, due to the lack of time, all the partial palmprints are compared only to a single full palmprint, which is the second full palmprint image out of the eight full palmprints, while in PP-RIDER, all the partial palmprints are compared with the all these eight full palmprint images. Therefore, one can expect a better result when the partial palmprints are compared with all the full palmprints in the database, which is happened for the PP-RIDER technique.

5.3. **EXPERIMENT 3: Partial palmprints with noise, without blur**

In this experiment first the partial palmprint images are degraded with white additive Gaussian noise, of zero mean and 0.04 standard deviation and then, they are
compared with the registered full palmprint images. These parameter values are taken from the original paper of MPOC technique [24].

Recognition results for PP-RIDER are shown in Table 6 and Table 7, with both the databases while Table 7 shows the recognition result for the PP-RELIF technique with only PV-TEST-PARTIAL database.

Table 6: Recognition results of PP-RIDER in the presence of Gaussian noise for modified THUPALMLAB database.

<table>
<thead>
<tr>
<th>Experiment3: With noise and no blur (modified THUPALMLAB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PP-RIDER (size: 11×11)</td>
</tr>
<tr>
<td>-------------------------</td>
</tr>
<tr>
<td>EER (%)</td>
</tr>
<tr>
<td>$d'$</td>
</tr>
</tbody>
</table>

Table 7: Recognition results of both the techniques in the presence of Gaussian noise for PV-TEST-PARTIAL database.

<table>
<thead>
<tr>
<th>Experiment3: With noise and no blur (PV-TEST-PARTIAL)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PP-RIDER (size: 11×11)</td>
</tr>
<tr>
<td>-------------------------</td>
</tr>
<tr>
<td>EER (%)</td>
</tr>
<tr>
<td>$d'$</td>
</tr>
</tbody>
</table>

From the Table 6, it can be seen that both the increased sizes (61×61 and 101×101) of inside-lobe have the better performances than the original size (11×11) for the PP-RIDER. Among the increased sizes, the one with inside-lobe of size 61×61 has even better performance than one with size 101×101, indicating the presence of some significant spurious peaks after the 61×61 dimension. Compared to the experiment 2 and Table 4, the present results are poorer but with not a big difference for the modified THUPALMLAB database. This shows the capability of the PP-RIDER technique to handle the Gaussian noise affected partial palmprint images.
However, this trend of improving the results as the size of the *inside-lobe* increases has not been observed for the PV-TEST-PARTIAL database as shown in Table 7 as the results start getting poor in terms of their EER values, although with a very small amount, as the sizes increase. On the other hand, their $d'$ values keep increasing indicating that although their recognition rate are decreasing (which is measured in EER) but the genuine and impostor distributions are getting more separated.

The PP-RELIF technique still has a poor performance compared to the PP-RIDER which is shown in Table 7 with the higher EER and $d'$ values.

**5.4. EXPERIMENT4: Partial palmprints without noise, with blur**

In the final experiment, partial palmprint images are degraded with motion blur with a length of 22 pixels and zero degree angle are considered, since the partial palmprint images are already randomly-rotated.

Table 8 and Table 9 show the recognition results for the PP-RIDER techniques with both the databases while Table 9 shows the results for feature-based technique with PV-TEST-PARTIAL database.

As can be seen from Table 8, the original *inside lobe* size $(11 \times 11)$ of the PP-RIDER has produced poor results in the present experiment, however, improvements over the results are achieved with the increased sizes $(61 \times 61$ and $101 \times 101)$. A similar trend can also be observed for PV-TEST-PARTIAL database in Table 9. Sizes $101 \times 101$ and $61 \times 61$ achieve the best results in both the databases, respectively. Compared to the experiment 2, poor results are obtained for the PP-RIDER technique, with a significant difference in the EER values.
Table 8: Recognition results of PP-RIDER in the presence of motion blur for modified THUPALMLAB database.

<table>
<thead>
<tr>
<th>Experiment3: Without noise and with blur (modified THUPALMLAB)</th>
<th>PP-RIDER (size: 11×11)</th>
<th>PP-RIDER (size: 61×61)</th>
<th>PP-RIDER (size: 101×101)</th>
</tr>
</thead>
<tbody>
<tr>
<td>EER (%)</td>
<td>49.820</td>
<td>38.581</td>
<td>38.576</td>
</tr>
<tr>
<td>$d'$</td>
<td>0.036</td>
<td>0.8738</td>
<td>0.8277</td>
</tr>
</tbody>
</table>

Table 9: Recognition results of both the techniques in the presence of motion blur for PV-TEST-PARTIAL database.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>EER (%)</td>
<td>37.132</td>
<td>36.368</td>
<td>38.675</td>
<td>50.115</td>
</tr>
<tr>
<td>$d'$</td>
<td>0.7159</td>
<td>0.6262</td>
<td>0.5179</td>
<td>0.065</td>
</tr>
</tbody>
</table>

A high EER and lower $d'$ indicate the inability of the PP-RELIF technique to handle this kind of degradation, as shown in Table 9. This may be explained because the blurring tends to change the values of the pixel and their neighbourhood by the smearing effect, and the descriptors of the interest points are generated by considering the local neighbourhood information.

Also, comparing the results of PP-RIDER and PP-RELIF techniques, it is again shown that PP-RIDER performed much better than PP-RELIF. May be having a single full palmprint registered in the database influences the results.
6. CONCLUSIONS AND FUTURE WORK

This thesis work proposes two novel partial-to-full palmprint recognition techniques, which are different in nature, i.e., one is Fourier-based and other is local invariant features-based. Both of these techniques are designed to handle random-rotation and degradation of the partial palmprints.

For the testing purposes, two databases are used: THUPALMLAB and PV-TEST-PARTIAL. However, since the THUPALMLAB database only contains high-resolution full palmprint images, a novel partial palmprint database, which is called modified THUPALMLAB, has generated by cropping the full palmprint images into four different regions (or segments). Later on, these partial palmprint images were subjected to arbitrary rotation to make the database even more challenging and realistic.

Four types of experimental testing were conducted under different scenarios: (a) Original MPOC and proposed PP-RIDER techniques are compared; (b) when no degradations; (c) when Gaussian noise and (d) when motion blurs were added to the partial palmprints of both the databases. Parameters for the Gaussian noise and motion blur were chosen to be the same as chosen in the paper proposing the original MPOC technique.

The Fourier-based technique (also known as PP-RIDER) combines the merits of FMT and MPOC technique. FMT is used for correcting the random-rotation of a probe partial palmprint with respect to a registered full palmprint and then, MPOC technique is used to calculate the similarity score between the aligned images. Furthermore, PP-RIDER uses three different sizes of inside-lobe for MPOC technique, which are: $11 \times 11$, $61 \times 61$ and $101 \times 101$. It has been observed there are always some spurious peaks around the main peak of the correlation plane; thus, this could affect the new peak value $m_{pec_{f,g}}$, which is the ratio of maximum values in the inside-lobe and outside-lobe. Improvement of the recognition performance over the original size (i.e. $11 \times 11$) than the new sizes (i.e. $61 \times 61$ and $101 \times 101$) can be seen from the experimental results. For example, in experiment 2 where partial palmprint images were not
degraded either with Gaussian noise or motion blur for both the databases, EERs are gradually decreasing, hence improvement over the recognition rate has been observed. Also, this improvement trend has been noticed, particularly for the modified THUPALMLAB database, when the partial palmprint images were degraded with white Gaussian noise and motion blur, which were performed in experiments 3 and 4. However, for the PV-TEST-PARTIAL database this trend failed to follow, particularly for the experiment 2. It is difficult to say anything concretely about the results of this database, since the size of the database is small. In addition, experiment 1 shows a clear advantage of using PP-RIDER when compared to the original MPOC when dealing with arbitrarily rotated partial palmprints.

Another novel technique, which is local invariant features-based (also known as PP-RELIF), is also proposed in this thesis. This technique first computes the interest points and its descriptors in both the input images (test partial palmprint and registered full palmprint images) by using a well-known SURF technique. These descriptors are partial invariant to illumination changes, scale changes, rotation changes and 3D viewpoint. In the feature matching stage, common interest points in the images are calculated and since, there is a possibility of inconsistent matches between them (outliers), they should be removed. To remove the outliers from the set, RANSAC technique is used and this algorithm outputs a set of inliers. Finally, for the matching process, an error measure is calculated which calculates the dissimilarities between the spatial arrangement of these inliers in both the images. Due to the lack of time, this technique is tested only with PV-TEST-PARTIAL database because of small scale and also, all the partial palmprints are compared with only second full palmprint of each user. Second full palmprint image is chosen, since it is the most complete image rest of other full palmprint images. Poor results are obtained for this technique for each of the cases when partial palmprints are subjected to: (i) no degradation; (ii) degradation by Gaussian noise and (iii) degradation by motion blur.

Some limitations of the current techniques were also identified which are: (i) handling arbitrarily rotated partial palmprints degraded with motion blur and (ii) a large
sensitivity to the intra-user variability observed in the high-resolution full palmprint images in both the databases.

Following are the future work on this thesis would involves

- Testing the proposed technique to a real-latent partial palmprint database.
- To perform an experiment when the partial palmprint images are degraded by both Gaussian noise and motion blurring, simultaneously.
- To handle the above mentioned limitations, a modification to the present techniques should be made which would provide more tolerance against the small changes in the palmprint image details and also, exploit both local and global information. This may be done by using a multimodal system which combines two or more algorithms, which are different in nature, at the score-level. For example, minutiae matching and PP-RIDER techniques can be combined at the score-level by using a weighted SUM-rule.
7. REFERENCES


[19] Z Sun, T Tan, Y Wang, and S. Z Li, "Ordinal palmprint representation for


[41] (2012) Benchmark Area: Palmprint Verification. [Online]. [https://biolab.csr.unibo.it/FvcOnGoing/UI/Form/BenchmarkAreas/BenchmarkAreaPV.aspx](https://biolab.csr.unibo.it/FvcOnGoing/UI/Form/BenchmarkAreas/BenchmarkAreaPV.aspx)


