Can we use *Second* Minor Finger Knuckle Patterns to Identify Humans?

Ajay Kumar, Zhihuan Xu
Department of Computing, The Hong Kong Polytechnic University
Hung Hom, Kowloon, Hong Kong
Email: ajaykr@ieee.org, zhihuan.xu@connect.polyu.hk

***Abstract*— Human hand possesses some of the most distinctive anatomical features which have been extensively used for the biometrics identification. However there are several hand features which results from complex interaction among bones, muscles, skin and tissues (therefore these are expected to be anatomically unique to individuals) which remain relatively unexplored for their potential in biometrics especially for forensic applications. This paper explores the possibility of using lowest finger knuckle patterns formed on the joints between metacarpal and the proximal phalanx bones for the biometrics identification. We automatically segment such region of interest from the hand images and normalize/enhance them to accommodate illumination, scale and pose variations resulting from the contactless imaging. The normalized knuckle images are used to match using several matchers popular in the literature. We use database of 110 different subjects acquired from the contactless hand imaging to ascertain the performance. We also evaluate the performance from matching of such lowest finger knuckle patterns using two session data acquired after an interval of at least two years. The experimental results are very encouraging and demonstrate potential of such unexplored finger knuckle patterns for the biometrics applications.**

Keywords- Hand Biometrics, Finger Knuckle Identification, Minor Finger Knuckle Recognitiong, Finger Dorsal Biometrics

I. INTRODUCTION

Biometrics features are increasingly employed for the human identification in commercial and forensics applications. The choice of a biometric modality for human identification largely depends on the nature of application and is restricted by anatomical piece of evidences available for the forensic analysis [1]. The fingerprint, finger-vein and finger knuckle images can be *simultaneously* acquired for the biometrics identification. In this context, the constrained imaging requirement associated with finger-vein acquisition can add to the cost and user inconvenience while integrating them with fingerprint based systems. However, the simultaneous acquisition of fingerprint and finger knuckle images can be achieved without any additional inconvenience to users, also at low cost, with simple addition of an external imaging camera to the existing (slap) fingerprint devices which can simultaneously acquires finger dorsal images and synchronizes the acquisition with external software. Therefore it is *important* to investigate on the uniqueness and stability in the pieces of information which can be recovered from the finger dorsal images. In addition, there are varieties of recorded forensic images (figure 1, [13]) in which only the finger dorsal features are available to establish the identity of a suspect. Automated or forensic identification of knuckle patterns has invited very little attention in the literature and several questions relating to uniqueness and/or stability of such patterns are yet to be answered. This paper focuses of such problem and investigates the possibility of using *second* minor finger knuckle patterns (figure 2) for the human identification.

Figure 1: Sample images in which the finger dorsal patterns can be used to ascertain identity of a suspect. The blue and red circles are added to point out the region of interest considered for the investigation in this work

II. MOTIVATION AND OUR WORK

The key objective of our work is to investigate the possibility of using finger knuckle patterns, formed between proximal and the metacarpal phalanx bones (metacarpophalangeal joints) of the fingers, for automated human identification. It may be noted that *prior* work available in the literature has investigated the finger knuckle patterns formed on finger dorsal surface joining middle phalanx and proximal phalanx bones (PIP joints), *e.g.* [2], [6]-[10], *etc*. There has also been some work on investigating knuckle patterns formed between distal and middle phalanx bones (DIP joints) reported in the literature [16]. However in the best of our knowledge there has not been any study to ascertain the possibility of exploiting knuckle patterns formed between metacarpal and the proximal phalanx bones (MP joints in figure 2) of fingers for the automated biometric identification. In this paper, we refer such knuckle patterns as the *second* minor finger knuckle patterns to distinguish with the *first* minor knuckle patterns formed on DIP joints and investigated in [16].

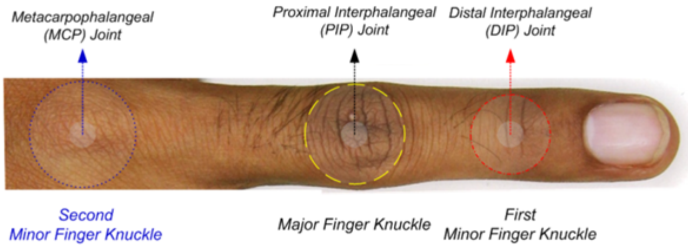


Figure 2: Sample finger dorsal images to illustrate prior work in finger knuckle identification and *second* minor finger knuckle patterns investigated in this work.

The motivation of this study is two folds: firstly the *second* minor knuckle patterns may be the only[†] piece of evidence available to ascertain the identity of suspect in several images available for forensic analysis. Therefore investigation into the uniqueness (also stability) of such minor finger knuckle patterns is vital for their usage in forensic identification of suspects. Secondly, such knuckle patterns can be simultaneously acquired using traditional finger knuckle imaging (or even during fingerprint imaging employed at border crossing, *e.g*. US-VISIT program [22] which uses slap fingerprint imaging devices, by providing additional camera for imaging finger dorsal surface) and used to further improve the performance from conventional finger knuckle (or even fingerprint) identification. The key contributions from this paper can be summarized as follows:

(a) This paper investigates the finger dorsal skin patterns formed between the metacarpal and the proximal phalanx bones of fingers for their possible use as biometrics trait. The uniqueness of such patterns is ascertained from experimental results, on the database of 110 subjects (550 images acquired using contactless imaging), which are highly promising.

(b) We develop completely automated method to segment such region of interest images from contactless hand imaging and use them to ascertain matching accuracy. This paper present experimental results from three matchers and evaluates their comparative performance. This paper also ascertains the *stability* of finger such *second* minor finger knuckle patterns using a set of images acquired after an interval of over 2 years.

The rest of this paper is organized as follows. Section III presents the details on completely automated approach for extracting region of interest (ROI) images. This is followed by brief discussion on the matchers employed for the *second* minor finger knuckle matching. Section V describes the experimental while the key conclusions from this paper are summarized in section VI

III. Finger Knuckle Imaging and Region of Interest Segmentation

The finger dorsal surface of right hand from the volunteers was acquired using contactless hand imaging. The imaging setup is similar to as the one employed in reference [2]. However the illumination for the imaging in this work was utilized from the (ambient) outdoor and indoor environment. Acquired images are firstly subjected to histogram equalization, binarization (Otsu's method followed by removal of isolated noisy pixels) and used to generate hand contour images as shown in figure 3. The key objective in this work is to evaluate the uniqueness and stability of second minor finger knuckle patterns which are formed on the skin surface above the middle phalanx and proximal bone joints of finger dorsal surface. Therefore the automated localization of key points from the hand contour images as described in reference [2] is performed and utilized in this work (not described here as this can be referred from [2]). The distance between hand held digital camera and the hand dorsal surface in contactless imaging is not fixed. Such variation in distances can generate palm dorsal images with varying scale and therefore scale normalization is performed. This is achieved by normalizing the acquired images to a fixed scale. The scale factor is computed from the ratio of distance between the two finger valleys (*v1* and *v3* in figure 3) and a fixed distance computed from the average of such finger valley distances from sample images (fixed to 325 in our experiments). The key points corresponding to (four) finger tips and mid-point of two base points for each of the

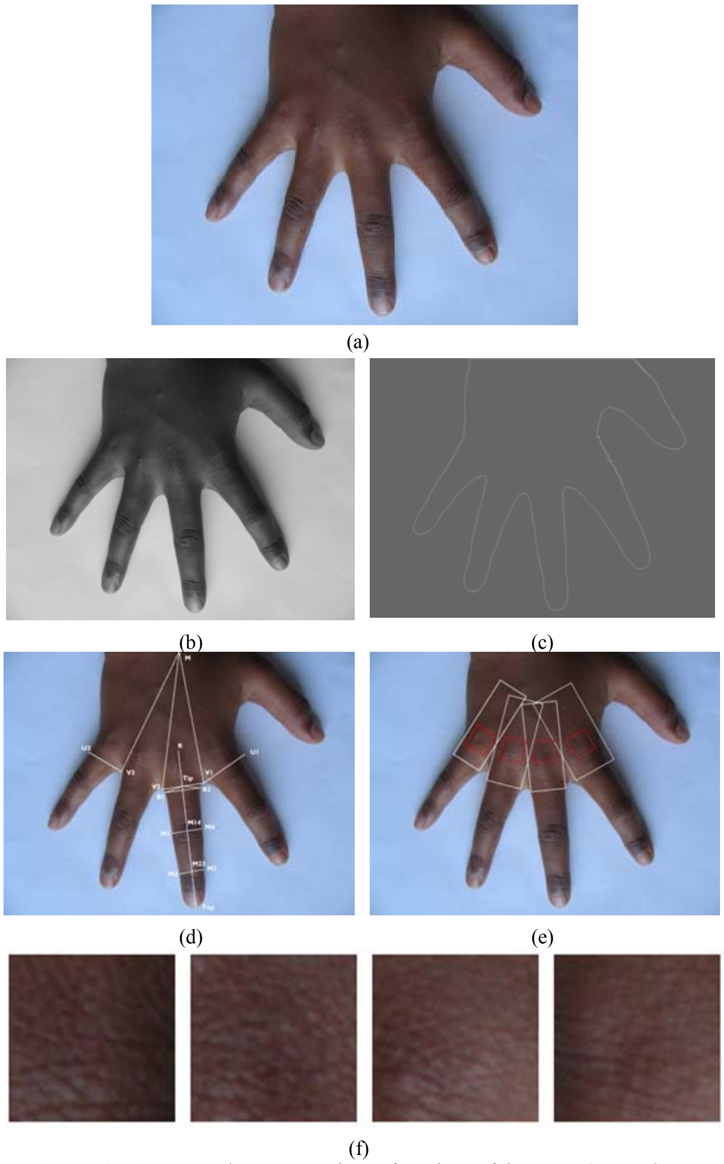
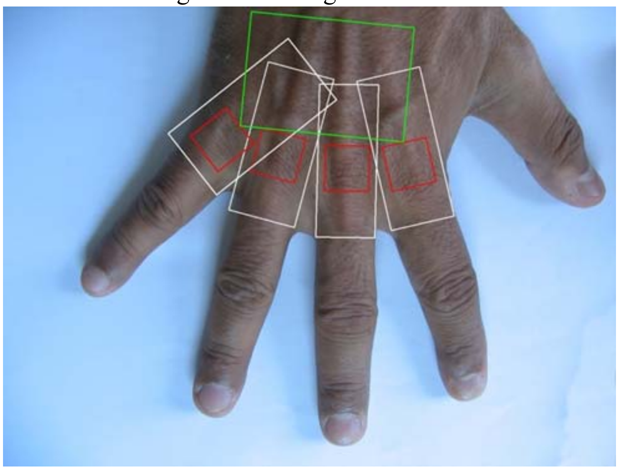


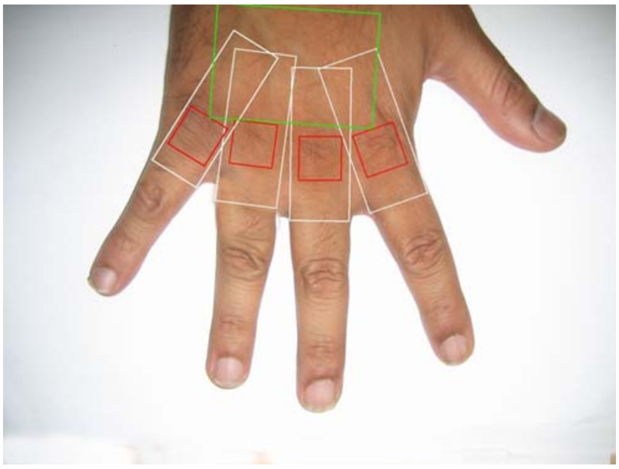
Figure 3: Automated segmentation of region of interest (*second* minor finger knuckle); (a) acquired image sample under outdoor illumination, (b) gray-level, and (c) recovered hand contour image for the localization of key points shown in (d). The red squares in figure (e) illustrate the localized *second* minor finger knuckle region and corresponding segmented knuckle images are shown in (f).

† There are known examples [21] of criminal investigations in which the knuckle patterns have been successfully used as a piece of forensic evidence for the prosecution of suspects.

finger are used to further localize the *second* minor finger knuckle region of interest. The line joining finger-tip (point *top*) and the base point (mid-point of *v1* and *v2*) is further extended by an amount one third of finger length (or by the distance between *M23* and *M14* in figure 3). This extended point (*R* in figure 3) is used as the center point of a 100 × 100 pixel square region which is automatically segmented as the *second* minor finger knuckle image. Figure 4 illustrate another two image samples and their automatically localized *second* minor finger knuckle regions as the red color boxes.



(a)



(b)

Figure 4: Image samples from two volunteers acquired under outdoor (a) and in indoor (b) environment. The red boxes illustrate automatically localized and segmented 100 × 100 pixels ROI to ascertain their possible usage as a biometric trait.

A. *Image Normalization*

The ROI images are acquired using contactless imaging and therefore there are significant illumination, pose and scale changes in the segmented images. The ambient illumination at the region of interest images is not uniform and the curved 3D knuckle surface often results in uneven reflection which generates shadow. Therefore non-linear image enhancement is employed to reduce undesirable effects from the contactless imaging. Each of the ROI is firstly divided into 10 × 10 pixel sub-blocks the average pixel level in these blocks is determined to estimate the (average) background illumination from each of the blocks. There block average is used to recover background illumination image of original size knuckle image by using bi-cubic interpolation [6]. This background illumination image is subtracted from the original grey level knuckle image and the resulting image is subjected to histogram equalization. The resulting images illustrate significantly enhanced contrast/illumination and are used for the feature extraction. The images shown in figure 5 (b and c) suggests that such enhancement approach has been quite effective to enhance knuckle creases and curves from the segmented knuckle images.

IV. FEATURE EXTRACTION AND MATCHING

The *second* minor finger knuckle images after enhancement illustrate random texture which appears to be quite unique in different fingers/subjects. This texture typically consists of creases, lines, and wrinkles of varying thickness, which also varies with the forward movement of fingers. In this work, we investigated several matching strategies which have been shown [6], [16]-[19] to be effective in matching palm or *major* finger knuckle patterns in the literature.

A. *Band Limited Phase Only Correlation*

The second minor finger knuckle images typically illustrate texture which are random but appears to be quite unique for each of the fingers. These texture patterns can be effectively matched from their similarity or correlation in spectral representations. Such an approach [16]-[17] *only* uses phase information recovered from the 2D discrete Fourier transform (DFT) of knuckle images. In order to minimize the influence noise, only a band of frequency in the DFT representation is employed for the matching. This approach in [17] is briefly summarized in the following.

The 2D DFT of two $P \times Q$ pixels normalized knuckle images, say $S_1(x, y)$ and $S_2(x, y)$, can be respectively represented as $F_1(k_1, k_2)$ and $F_2(k_1, k_2)$. Their 2D DFTs can be computed as follows:

$$F_1(k_1,k_2) = \sum_{x,y} S_1(x,y)\, e^{-\frac{i2\pi x k_1}{P}} e^{-\frac{i2\pi y k_2}{Q}} = B_{F_1} e^{-i\phi_{F_1}(k_1,k_2)} \quad (1)$$

$$F_2(k_1,k_2) = \sum_{x,y} S_2(x,y)\, e^{-\frac{i2\pi x k_1}{P}} e^{-\frac{i2\pi y k_2}{Q}} = B_{F_2} e^{-i\phi_{F_2}(k_1,k_2)} \quad (2)$$

where B_{F1} and B_{F2} are the amplitudes while $\phi_{F_1}(k_1,k_2)$ and $\phi_{F_2}(k_1,k_2)$ represent the phase component of normalized knuckle image $S_1(x, y)$ and $S_2(x, y)$ respectively. The cross correlation $C_{F_1F_2}(k_1,k_2)$ between two phase components from (1) and (2) is computed as follows:

$$C_{F_1F_2}(k_1,k_2) = \frac{F(k_1,k_2)\overline{F_2(k_1,k_2)}}{|F_1(k_1,k_2)F_2(k_1,k_2)|} = e^{-i\{\phi_F(k_1,k_2)-\phi_{F_2}(k_1,k_2)\}} \quad (3)$$

where $\overline{F_2(k_1,k_2)}$ is the complex conjugate of $F_2(k_1,k_2)$ and $\{\phi_{F_1}(k_1,k_2) - \phi_{F_2}(k_1,k_2)\}$ represents the difference in phase components between two matched knuckle images. The phase only correlation between two knuckle images is estimated from inverse 2D DFT of $C_{F_1F_2}(k_1,k_2)$ as follows:

$$c_{I_1I_2}(x,y) = \frac{1}{PQ}\sum_{k_1k_2} C_{F_1F_2}(k_1,k_2)\, e^{i2\pi x k_1/P} e^{i2\pi y k_2/Q} \quad (4)$$

The band limited correlation between phase representations from two images is obtained by limiting k_1 and k_2 in (4) to some limit instead to P and Q respectively.

B. Local Radon Transform

This approach of matching knuckle using Local Radon Transform (LRT), referred to as RLOC [19] or *KnuckleCode* representation in [6], has shown to be very effective in matching major knuckle patterns and was therefore also attempted in this work. This approach effectively encodes the local orientation of curved lines and knuckle creases into one of the dominant orientations which is represented using a three bit binary code and such binarized templates is matched using the Hamming distance. The details of this approach can be found in reference [6] and [19]. The key advantage of this approach is that it produces smallest template size and is computationally efficient than other two methods considered in this work.

C. Ordinal Representation

The ordinal measures typically compute measurements that are based on the relative distances [20]. The ordinal representation of textured like surface such as palm and iris has shown to achieve promising results and therefore this method was also attempted to ascertain accuracy in matching knuckle images. Similar to as detailed in [18] two orthogonal Gaussian filters oriented at 0, 30 and 60 degrees are utilized to generate binarized feature templates. The Hamming distance between resulting feature templates is employed to generate match scores between the knuckle images.

V. Experiments and Results

In this work, we employed palm dorsal images from 110 different subjects using contactless imaging for the experiments. The images were acquired from the right hand of the volunteers in indoor or outdoor environment. All the acquired images were used to automatically segment 100 × 100 pixel ROI corresponding to second minor finger knuckle region as described in section 3. These images were enhanced and subjected to the feature extraction using three matchers as discussed in section 4. The band limiting threshold for BLPOC was fixed to 0.6 for all the experiments. The line width and length of one and seven pixel was respectively fixed for all experiments in RLOC (the filter size was 11 × 11). Two Gaussian filters (δ_x = 3, δ_y = 1) of size 11 × 11 pixels were utilized to compute ordinal representations of the segmented knuckle for the matching. Figure 5 illustrates some sample knuckle images and corresponding template images for respective enhanced knuckle images. We utilized four images for the training and remaining images for the testing. This was repeated for all the combination (leave out one protocol) of images used as test images. Therefore 550 (110×5) genuine scores and 299750 (109×5×5×110) impostor scores were computed for

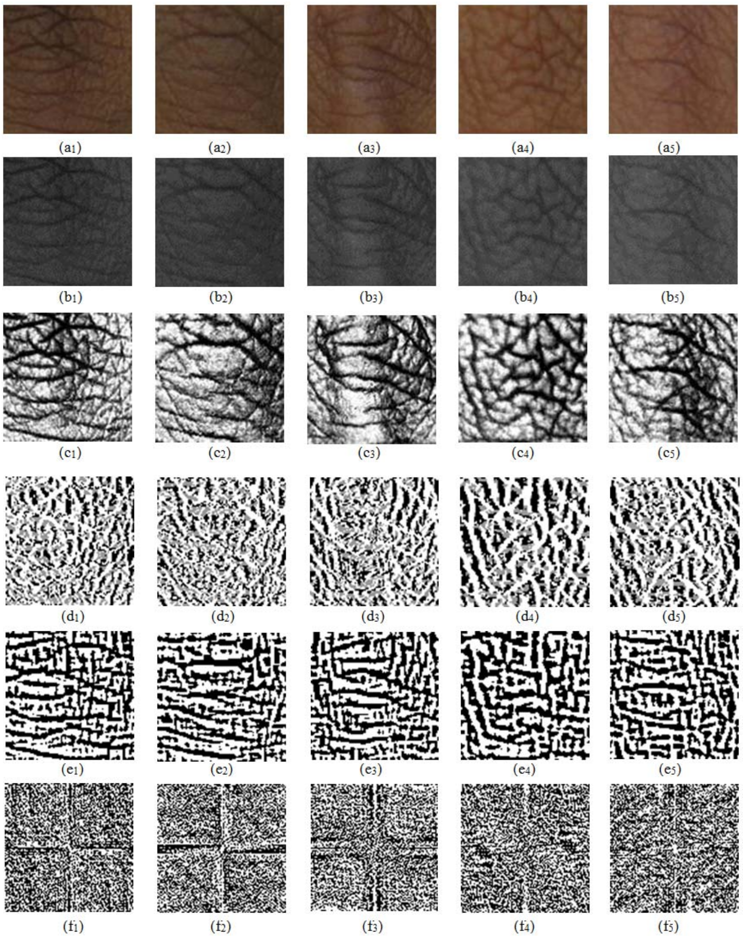


Figure 5: Automatically segmented lower or *second* minor knuckle images corresponding to middle finger images of five different subjects in (a_1-a_5). Corresponding grey-level images are shown in (b_1-b_5), enhanced images in (c_1-c_5), *KnuckleCode* or RLOC representation in (d_1-d_5), Ordinal representation for 30 deg (e_1-e_5), and spectral representation using BLPOC are shown in (f_1-f_5).

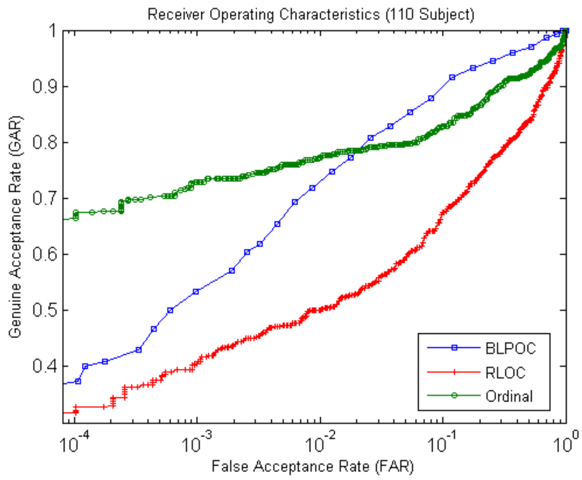


Figure 6: The ROC for matching *second* minor finger knuckle images from *index* fingers of 110 subjects.

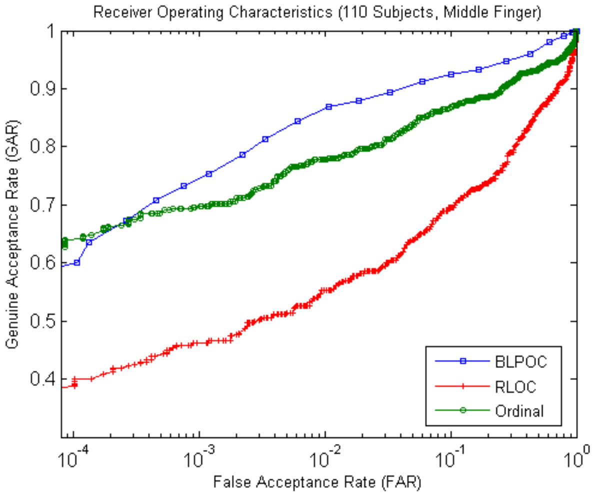


Figure 7: The ROC for matching *second* minor finger knuckle images from *middle* fingers of 110 subjects.

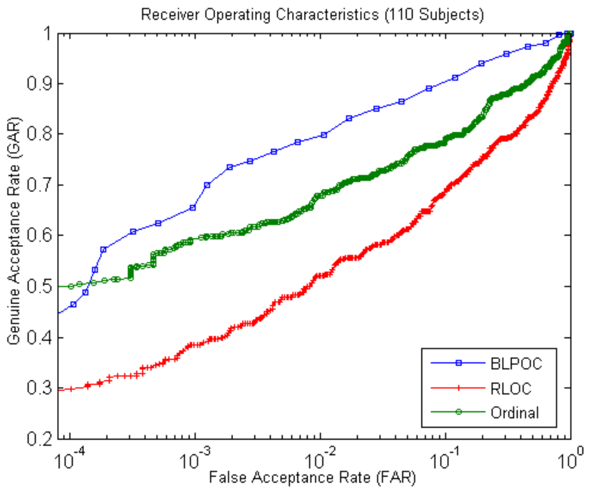


Figure 8: The ROC for matching *second* minor finger knuckle images from *ring* fingers of 110 subjects

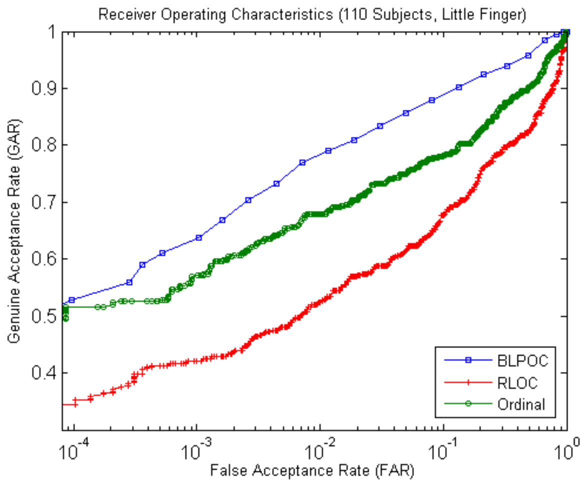


Figure 9: The ROC for matching *second* minor finger knuckle images from *little* fingers of 110 subjects.

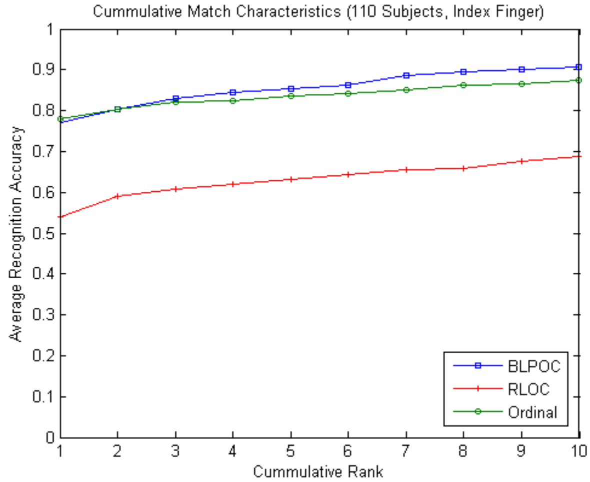


Figure 10: The CMC for matching *second* minor finger knuckle images from *index* fingers of 110 subjects.

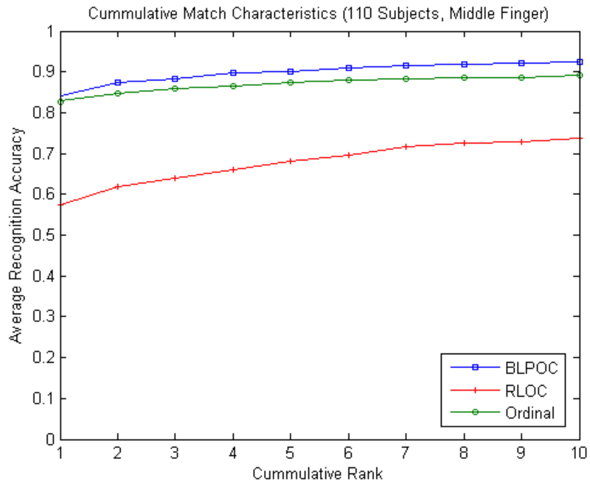


Figure 11: The CMC for matching *second* minor finger knuckle images from *middle* fingers of 110 subjects**.**

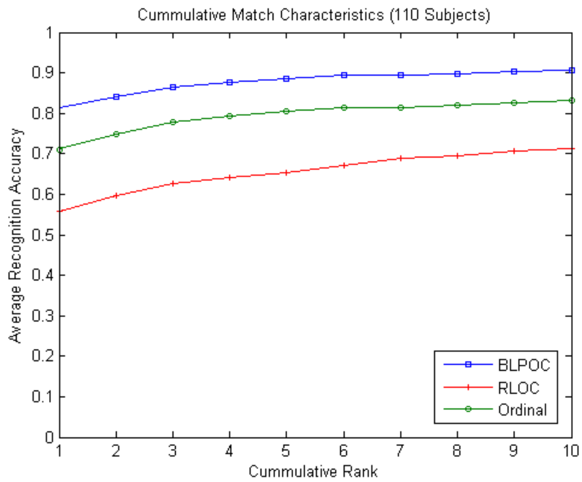


Figure 12: The CMC for matching *second* minor finger knuckle images from *ring* fingers of 110 subjects.

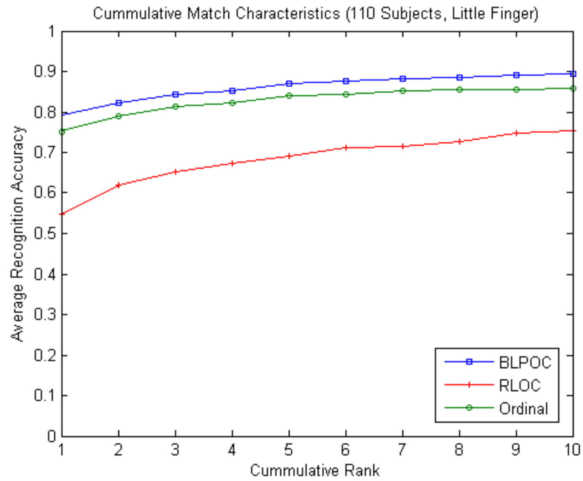


Figure 13: The CMC for matching *second* minor finger knuckle images from *little* fingers of 110 subjects.

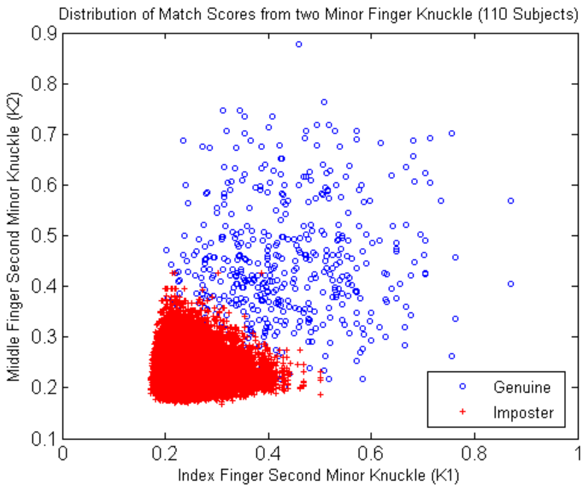


Figure 14: Distribution of genuine and impostor match scores from index and middle finger of 110 subjects which suggest further performance improvement while combining *second* minor finger knuckle images from these two (or more) fingers

generating the receiver operating characteristic (ROC). The ROC corresponding to the *index*, *middle*, *ring* and *little* finger is shown in figure 6, 7, 8 and 9 respectively. It can be ascertained that the BLPOC matcher performs the best among three matchers considered in this work. The best performance was achieved from second minor finger knuckle corresponding to the middle finger (achieves equal error rate of (8.36%). The cumulative match characteristics (CMC) corresponding to the each of the *index*, *middle*, *ring* and *little* finger is shown in figure 10, 11, 12 and 13 respectively. The BLPOC matcher also achieves superior performance for the recognition and achieves average rank-one recognition of over 80%. Figure 14 illustrates the plot of genuine and imposter match scores corresponding to the index and middle finger *second* minor knuckle images. This figure suggests that the combination of two such finger knuckle match scores can be used to achieve further performance improvement and should be explored in further work.

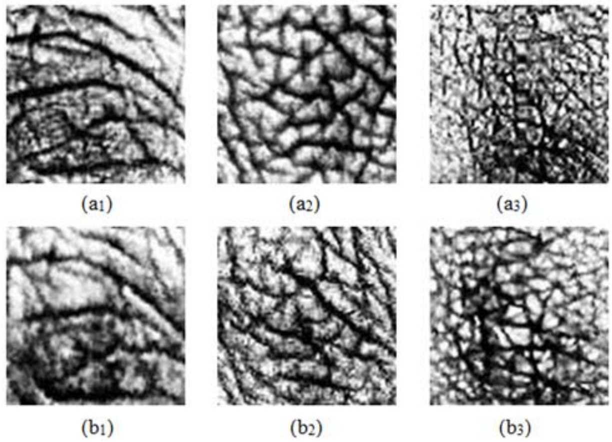


Figure 15: Enhanced image samples corresponding to three different subject's *second* minor finger knuckle images acquired over an interval of 2 years. These image samples not only illustrate stability of knuckle creases or patterns *but* also include the variations introduced due to contactless imaging under ambient illumination.

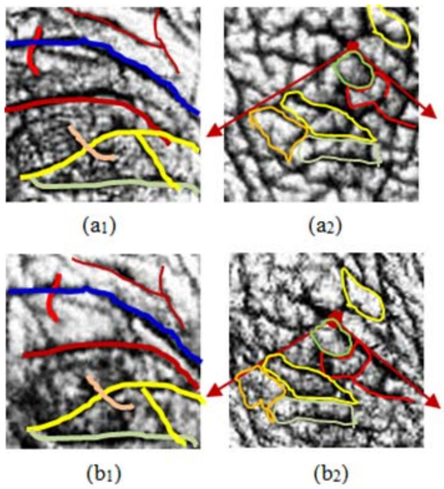


Figure 16: Manual matching of *second* minor finger knuckle patterns for the first two subjects in figure 15. The knuckle curves and creases are easy to be matched for subject a_1, but more difficult for subject a_2 and a_3 (match is not shown).

In order to ascertain the stability of *second* minor finger knuckle patterns we acquired palm dorsal images of ten subjects after an interval of at least two years. Some of these images are shown in figure 15-16. Some subjects in this dataset were students in teenagers who has noticeable physiological growth while some were in mid-thirties (figure 16 - a_1) whose knuckle lines and creases were relatively stable to be observed and matched manually. We also attempted to ascertain the matching accuracy from matching two (but long) session images. The number of genuine scores in this set of experiments was 50 (10×5) while the number of impostor scores was 450 (10×5×9). The ROC corresponding to four different fingers are shown in figure 17. It should be noted that the error or degradation in performance is not *just* due to alterations in knuckle patterns but also due to localization and segmentation errors in the lower quality images acquired under contactless imaging. The figures 15-16 underline the need for further work to develop matching techniques to accommodate knuckle curve and crease deformations.

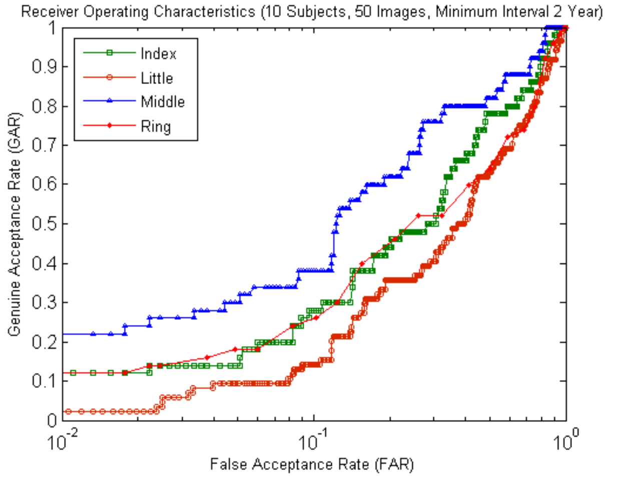


Figure 17: The ROC from two session database acquired after an interval of 2 years (minimum) and maximum of 4 years. The ROC from the pest performing matcher suggests that middle finger second minor finger knuckle achieves superior performance.

VI. Conclusions and Further Work

This paper has investigated the possibility of using *second* minor finger knuckle image for the personal identification. The approach described in this paper is completely automated and uses contactless imaging which is expected to produce/accommodate large variations in images. The experimental results presented in this paper from the database of 110 subjects are quite promising; rank-one recognition accuracy of over 80% (equal error rate of 8.36% for middle finger knuckle images) from *second*/single minor knuckle matching. Our experimental results suggest that spectral domain matching of knuckle patterns from their correlation in phase components achieves the best performance. Superior performance due to such band limited phase components can be possibility due to the fact that spurious high frequency components in knuckle images are better eliminated during the band limiting process which can generate more reliable matches based on slowly varying knuckle curves/creases.

The strength of this work is in completely automated evaluation of *second* minor knuckle patterns which have not yet attracted attention in biometrics. The attempt to match *second* minor knuckle patterns has generated promising results but requires further work to improve accuracy in such matching. The knuckle patterns can be fused to achieve further performance improvement and this is quite expected but need to be illustrated in further work.

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