IEEE Transactions on Information Forensics and Security
Vol. 9, pp. 1288-1298, August 2014

Importance of Being Unique from Finger Dorsal Patterns: Exploring Minor Finger Knuckle Patterns in Verifying Human Identities*

Abstract: *Automated biometrics identification using finger knuckle images has increasingly generated interest among researchers with emerging applications in human forensics and biometrics. Prior efforts in the biometrics literature have only investigated the 'major' finger knuckle patterns that are formed on the finger surface joining proximal phalanx and middle phalanx bones. This paper investigates the possible use of 'minor' finger knuckle patterns which are formed on the finger surface joining distal phalanx and middle phalanx bones. The 'minor' finger knuckle patterns can either be used as independent biometric patterns or employed to improve the performance from the major finger knuckle patterns. A completely automated approach for the 'minor' finger knuckle identification is developed with key steps for region of interest segmentation, image normalization, enhancement and robust matching to accommodate image variations. This paper also introduces a new or first publicly available database for 'minor' (also major) finger knuckle images from 503 different subjects. The efforts to develop automated 'minor' finger knuckle pattern matching scheme achieve promising results and illustrate its simultaneous use to significantly improve the performance over the conventional finger knuckle identification. Several open questions on the stability and uniqueness of finger knuckle patterns should be addressed before any knuckle pattern/image evidences can be admissible as supportive evidence in the court of law. Therefore this paper also presents a study on the stability of finger knuckle patterns from images acquired with an interval of 4-7 years. The experimental results and the images presented in this paper provide new insights on the finger knuckle pattern and identify the need for further work to exploit finger knuckle patterns in forensics and biometrics applications.*

1. Introduction

Automated identification of humans using their unique anatomical characteristics has been increasingly investigated for their applications in human surveillance and image forensics.

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Emerging national ID programs that require accurate, online and large scale identification automated personal identification have posed new challenges for the biometrics technologies. The unique identification project [4] is one such ambitious project that aims to identify ~1.2 billion population using ten fingerprints and two iris images. Selection of biometrics modalities in such large scale identification problems is not only limited by the individuality of the modality but also by the user-convenience in acquiring the respective modality. In this context, the finger-vein and finger knuckle images can be *simultaneously* acquired while acquiring the fingerprint images and with no additional inconvenience to the users. Simultaneous acquisition of finger-vein images [5] can however require some alterations in the existing (slap) fingerprint devices, largely due to the near infrared based intrusive imaging requirements for finger-vein imaging. However, the finger knuckle images can be simultaneously acquired with the addition of an external imaging camera that simultaneously acquires finger dorsal images and synchronizes the

Figure 1: Sample photographs with knuckle patterns during (a) sexual/physical assault, (b) kidnapping, (c) covert video and surveillance, (d) gesture [24], and (e)-(f) emotions [25] for surveillance and forensic applications.

acquisition with external software. Therefore it is important to ascertain the nature of information that can be extracted from the finger dorsal images. This paper focuses on this problem and investigates the possibility of using *minor* finger knuckle patterns for the biometric identification.

Accurate identification of finger knuckle patterns can be beneficial for several applications involving forensic and covert identification of suspects[†]. There are several classes of forensic images in which the finger knuckle patterns are the *only* piece of evidence available to identify the suspects. Figure 1 shows some examples of the photographs in which the finger knuckle pattern is the only or major source of information available to scientifically ascertain the identity of individuals. Therefore the matching of finger knuckle patterns can help to identify the suspects and ascertain supportive scientific evidence from the photographs, especially in cases when no information regarding fingerprint or face is present in the available photographs. The legal issues relating to the reliability of finger knuckle image patterns will largely be judged in the courtrooms. Therefore any new biometric to be introduced for the human identification should also meet the requirements stipulated by courts to be deemed admissible. Such requirements can vary among different courtrooms but often require reliable and repeatable measurements. It is therefore important that any new/potential biometric evidence to be admissible by court, in addition to their uniqueness, their stability over a reasonable time period should also be established. A preliminary study presented in this paper is motivated to check the veracity of the questions and assertions (we received during peer reviews on earlier papers [3], [7]) that the stability of finger knuckle patterns, especially for forensic and law-enforcement has never been explored/established.

[†] One example relating to the successful use of finger knuckle images as forensic evidence is the prosecution of Dean Hardy in 2012 [29]. The forensic anthropologist found that the distinctive finger knuckle (freckles) on the fingers of a hand seen in images of abuse were the same as Hardy's.

A normal human hand has four fingers each of which has 3 bone segments and 3 joints. The thumb has 2 bone segments and 2 joints. These segments are known as phalanges (plural of phalanx) and are shown in figure 2 from a typical finger dorsal image. While in some humans the major finger knuckle pattern can be occluded by hair, the *minor* finger knuckle patterns do not appear to suffer from such problem. There are several forensic images when only *minor* finger knuckle patterns/portions are visible/available for any possible identification. In addition, the matching results from the *minor* finger knuckle matching can also be employed to improve the reliability and accuracy of conventional/emerging major finger knuckle based biometric identification.

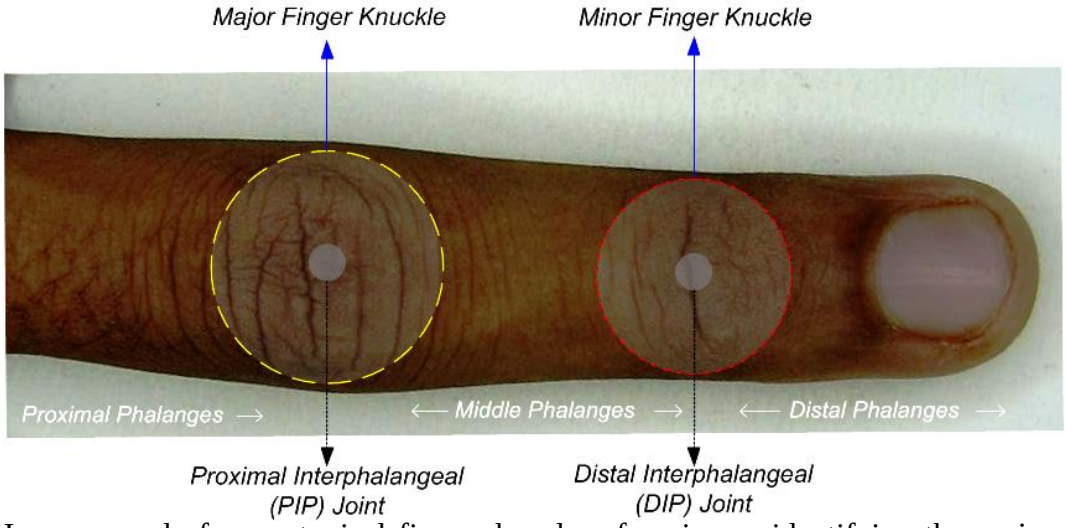


Figure 2: Image sample from a typical finger dorsal surface image identifying the *major* and *minor* knuckle pattern regions with respect to the MCP/DIP joints.

1.1 Motivation and Related Work

The use of finger knuckle images for the biometrics identification has generated increasingly interest in the literature. Woodard and Flynn [1] successfully demonstrated the use of 3D finger dorsal images for personal identification. This work essentially exploits local curvature patterns on the 3D finger surface and quantifies them into various shape indexes for the matching. Reference [3] details an online system using the hand dorsal surface images which can simultaneously exploit the finger knuckle patterns from the multiple fingers and their

geometrical shape characteristics. There are several publications which have exploited the effectiveness of finger knuckle patterns using contactless imaging [1], [3], [7], [9] and contact based[‡] or constrained imaging [8], [11] [17]. These references in the literature have however exploited major finger knuckle images which capture patterns formed on the finger dorsal surface joining proximal phalanx and middle phalanx bones. In the best of our knowledge, there are no known efforts to exploit *minor* finger knuckle patterns (figure 1) which are formed on the finger dorsal surface joining distal phalanx and middle phalanx bones.

The unidirectional bending of fingers is primarily responsible for generating skin pattern alterations on the finger dorsal surface joining the four phalanx bones. The *minor* finger knuckle patterns are formed on the surface joining distal phalanx and middle phalanx bones and can also be quite distinctive for biometrics identification. This paper [23] has attempted to examine biometric identification capability for humans using such *minor* finger knuckle images and develops effective algorithms for the automated segmentation of region of interest, image normalization, enhancement and robust matching to accommodate inherent image variations.

Key contributions from this paper can be summarized as in the following:

(a) This paper investigates on the possibility of using *minor* finger knuckle patterns for human identification. A completely automated scheme to simultaneously segment *minor* and major finger knuckle images from contactless finger dorsal images is developed. Combination of simultaneously acquired *minor* finger knuckle pattern and major finger knuckle pattern images can achieve significant improvement in performance, which is not possible by using major finger knuckle images alone as in the literature.

(b) Lack of any systematic study to ascertain stability of knuckle patterns raises several questions on the possible use of finger knuckle patterns in image forensics for law

[‡] Unlike fingerprint and palmprint images, there are no known examples of using inked impressions for the finger knuckle patterns to identify humans. Therefore *finger knuckle* identification, instead of *finger-knuckle-print* identification has been justified and used in several earlier publications [3], [7], [9].

enforcement and civilian applications. This paper therefore also presents a/first study (also publicly providing such images for further investigation) to ascertain the stability of knuckle pattern in finger dorsal images acquired over the interval of over 6 years. Such study is especially important for forensic analysis of those images in which finger knuckle is the only piece of evidence available to identify the suspects.

(c) This paper provides first publicly available database on *minor* knuckle images (also major finger knuckle images), from 503 different subjects. In the best of our knowledge this will be largest subject's database available to-date in public domain and help to advance further research efforts in this area.

The rest of this paper is organized as follows. Section 2 describes completely automated approach to segment the minor finger knuckle images from finger dorsal images acquired using contactless imaging setup. This section also includes details on the scale correction and image enhancement. This is followed by the details of the feature extraction approaches that were considered in this paper in section 3. Section 4 briefly describes various match score combination schemes exploiting minor and major finger knuckle patterns. Section 5 details the experiments and achieved results from the investigated approach in this paper. The study relating to the stability of finger knuckle patterns appears in section 6. Finally, the key conclusions from this paper are summarized in section 7.

2. Image Segmentation and Normalization

Accurate personal identification using minor finger knuckle patterns will require accurate segmentation of region of interest images. The segmentation approach should be able to generate normalized and fixed size region of interest images from the finger dorsal images of subjects under varying age group. In absence of any fixation pegs or the finger docking frame, the acquired finger dorsal images illustrate fingers with varying poses, locations and scale changes. In addition, the varying length of fingers, finger-widths, finger-nails, skin pigmentation and

location of distal interphalangeal points, poses severe challenges to exploit any anatomical characteristics of fingers for robust minor finger knuckle segmentation. Figure 3 illustrates simplified block diagram for the finger knuckle segmentation strategy attempted in this work to segment fixed size minor finger knuckle images.

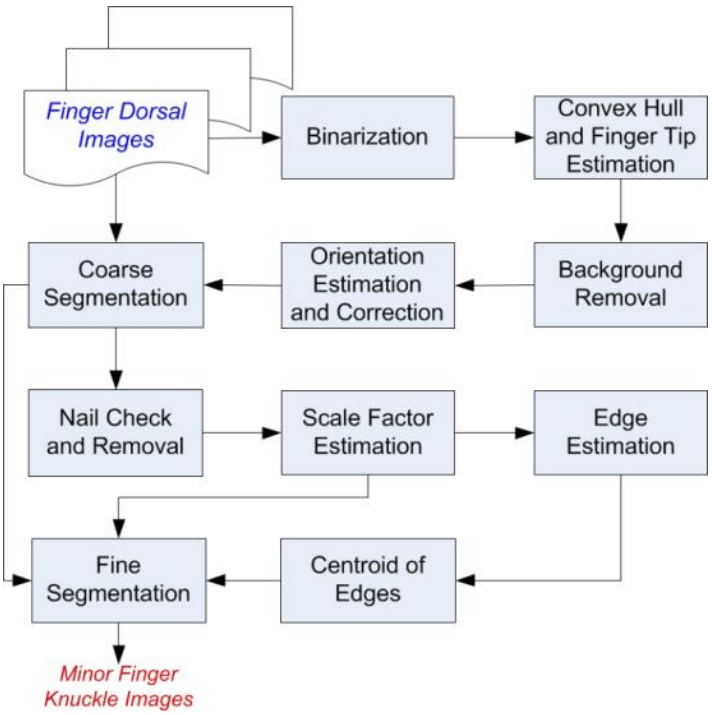


Figure 3: Simplified block diagram illustrating key steps in the automated segmentation of *minor* finger knuckle images from the finger dorsal images.

Each of the acquired images is firstly subjected to binarization using Otsu's thresholding. The resulting images are cleaned (denoised) by automatically removing the isolated regions/pixels (< 100 pixels) so that the longest object representing finger is only retained. The binarized finger shape is used to estimate the location of finger-tip from the convex hull of the images. The location of finger-tip is utilized to eliminate the background image above the finger tip. The orientation of fingers is then estimated from this binarized image using the methods of moment, similar to as also employed in [5]. This step is followed by the coarse segmentation which segments a small portion of acquired finger images that can include minor finger knuckle region while excluding major knuckle region and major part of finger nail. Such segmentation

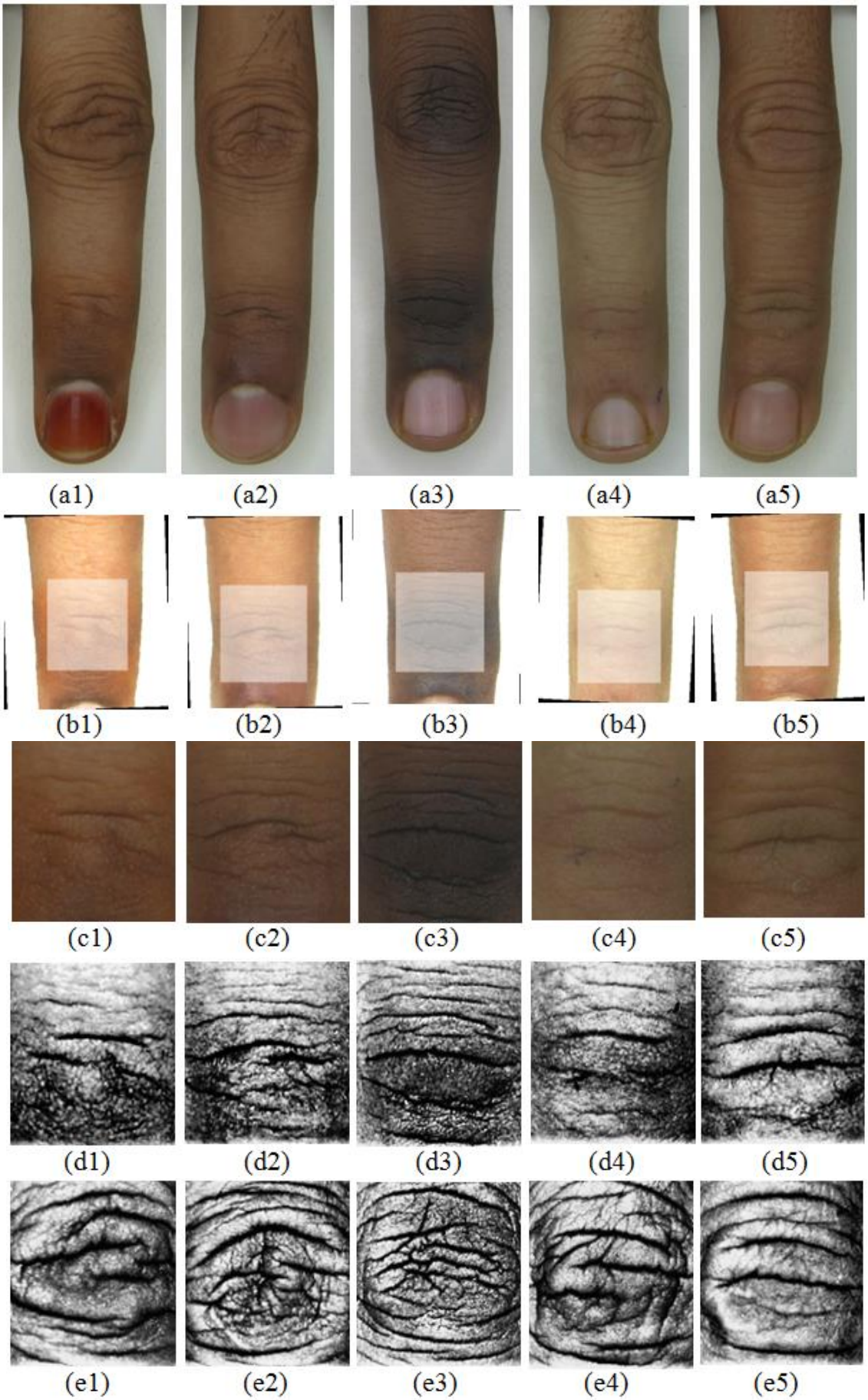


Figure 4: Finger dorsal images in (a1)-(a5), corresponding *minor* finger knuckle region identified for segmentation during fine segmentation in (b1)-(b5), segmented *minor* finger knuckle images in (c1)-(c5), images after enhancement in (d1)-(d5), respective segmented and enhanced major finger knuckle images in (e1)-(e5).

strategy requires some crude assumptions for the maximum ratio of nail length to the finger length and assumption that the major finger knuckle region is located somewhere in the middle of the acquired finger dorsal image. The resulting coarsely segmented image is further subjected to nail check and removal steps which consist of segmenting the image and locating the bonding box region for smaller parts and removing them. The width of the resulting image is computed and used to estimate the scale factor for the scale normalization. The edge detection of resulting image is used to locate the center of minor finger knuckle image. This is achieved by estimating the location of the centroid for the resulting edge detected image and segmenting a fixed size region (160 × 180 pixels) that represents minor finger knuckle region for the finger dorsal image.

2.1 Image Enhancement

The finger dorsal surface is 3D curved surface and such curves can result in uneven illumination reflections and shadows. Therefore the segmented minor finger knuckle images often have low contrast and illumination variations. The enhancement steps are essentially required to normalize such illumination variations. The illumination normalization approach used in this work is same as also used in [7]. This approach firstly estimates the average background illumination in the 16 × 16 pixels sub-blocks of the segmented knuckle images. The estimated illumination is then subtracted from the original knuckle image to remove the uneven illuminations. The resulting image is then subjected to the histogram equalization operation which generates enhanced minor finger knuckle image for the feature extraction stage. Figures 4 (d1)-(d5) shows image samples after the image enhancement operations.

3. Feature Extraction and Matching

The finger knuckle images after enhancement typically represent some *random* texture pattern which *appears to be* quite unique in different fingers. Therefore a variety of spatial and spectral domain feature extraction strategies can be pursued to ascertain the matching accuracy from the minor finger knuckle images. The experimental results in this paper have employed local binary patterns [12], improved local binary patterns [13], band limited phase only correlation [19] and

1D log-Gabor filter based matchers [14]-[15] for the performance evaluation. These matchers are briefly described in the following.

<u>Local Binary Patterns</u>

The local binary patterns (LBP) encoding can acquire local knuckle patterns and also represent multi-scale texture appearances. The binary patterns for every pixel centered at z_c, with neighboring/surrounding pixels z_p, is computed as follows [12]:

$$h(z_p - z_c) = \begin{cases} 1, & z_p - z_c \geq 0 \\ 0, & Otherwise \end{cases} \quad (1)$$

The LBP code for the corresponding pixel z_c is generated by assigning binomial weight 2^p to the above function/equation.

$$LBP(z_r) = \sum_{p=0}^{P-1} h(z_p - z_c)\, 2^p \quad (2)$$

where P is the total number of pixels in a local region and $p = 0, 1, 2, \ \ldots \ P - 1$. The LBP encoded knuckle images are used to generate LBP descriptors using local histograms. The histogram information from each of the local regions is concatenated to extract the LBP descriptors. The similarity between two LBP descriptors is computed by comparing histogram intersection similarity measure as follows:

$$S_G^{1,2} = \sum_{i=1}^{W} min(g_i^1, g_i^2) \quad (3)$$

where W is the number of histogram bins while g^1 and g^2 represent LBP descriptors from the enhanced knuckle images.

There are several variants of LBP that may be explored for the matching of knuckle image patterns. Improved LBP (ILBP) [13] is one such variant that uses *mean value* of neighborhood pixels for binarization (1), instead of center value used in LBP, and has also been investigated in this work. The ILBP enables us to utilize the gray level of center pixel and may deliver superior performance as the resulting LBP descriptor becomes more robust to the noise influencing the center pixel.

<u>1-D Log-Gabor Filter</u>

The experimental results in this paper are also reported using 1-D log-Gabor filter based feature extraction approach that can exploit local phase information from the enhanced finger knuckle images. Each of the segmented knuckle images were filtered by 1-D Log-Gabor filter $H(\omega)$ defined as follows:

$$H(\omega,\varphi) = e^{-\frac{(\ln(\omega/\omega_0)^2}{2\left(\ln(2\pi\sigma_f/\omega_0)\right)^2}} . e^{-\frac{(\varphi-\varphi_0)^2}{2\sigma_\varphi^2}} \tag{4}$$

where ω_0 is the central frequency, φ_0 is the orientation, σ_f and σ_φ are the constants that respectively determine radial and angular bandwidth of the log-Gabor filter. The filtered knuckle images are employed to extract the local phase information similar to as detailed in [14]-[15]. The matching scores between the any two knuckle images were generated by using the normalized Hamming distance S_{PQ} between their respective complex binarized templates as follows:

$$S_{PQ} = \frac{\sum_{x=1}^{X}\sum_{y=1}^{Y}\{P_r(x,y)\oplus Q_r(x,y) + P_i(x,y)\oplus Q_i(x,y)\}}{2\times X\times Y} \tag{5}$$

where P and Q are the two $X \times Y$ size complex bitwise knuckle template and $\oplus$ is the Hamming distance operator. The bit-wise shifting of knuckle templates, *i.e.* left-right (36 pixels) and top-bottom (36 pixels), is employed during the matching as it significantly helps to account for the translational errors in during the image localization. The center wavelength of 46, orientation φ same as φ_0, and the $2\pi\sigma_f/\omega_0$ ratio was empirically fixed to 0.55 for the 1-D log-Gabor filters employed in this work.

Band Limited Phase Only Correlation

One of the most effective approaches for matching two textured-like biometric images is to establish their *similarity in spectral domain* [2] representation using the phase information [16], [27]. The phase information using such phase only correlation approach can be extracted from the 2-D discrete Fourier transform (DFT) for each of the two images. In order to minimize the influence from matching of spurious phase components in the two images, only a band of

frequency in the DFT representation is utilized for the matching. Such an approach is referred to as band limited phase only correlation (BLPOC) and is briefly described in the following.

The 2D DFT of two normalized knuckle images, say $I_1(x, y)$ and $I_2(x, y)$ each with size $N \times M$ pixels, can be respectively represented as $D_1(k_1, k_2)$ and $D_1(k_1, k_2)$. The 2D DFTs can be computed as follows:

$$D_1(k_1, k_2) = \sum_{x,y} I_1(x, y)\, e^{-i2\pi x k_1/N} e^{-i2\pi y k_2/M} = B_{D_1} e^{-i\phi_{D_1}(k_1,k_2)} \quad (6)$$

$$D_2(k_1, k_2) = \sum_{x,y} I_2(x, y)\, e^{-i2\pi x k_1/N} e^{-i2\pi y k_2/M} = B_{D_2} e^{-i\phi_{D_2}(k_1,k_2)} \quad (7)$$

where B_{D_1} and B_{D_2} are the amplitudes, $\phi_{D_1}(k_1, k_2)$ and $\phi_{D_2}(k_1, k_2)$ are the phase component of normalized knuckle image $I_1(x, y)$ and $I_1(x, y)$ respectively. The cross correlation $R_{D_1D_2}(k_1, k_2)$ between two phase components of DFT representation from $D_1(k_1, k_2)$ and $D_1(k_1, k_2)$ can be computed as follows:

$$R_{D_1D_2}(k_1, k_2) = \frac{D_1(k_1,k_2)\overline{D_2(k_1,k_2)}}{|D_1(k_1,k_2)D_2(k_1,k_2)|} = e^{-i\{\phi_{D_1}(k_1,k_2)-\phi_{D_2}(k_1,k_2)\}} \quad (8)$$

where $\overline{D_2(k_1, k_2)}$ is the complex conjugate of $D_2(k_1, k_2)$ and $\{\phi_{D_1}(k_1, k_2) - \phi_{D_2}(k_1, k_2)\}$ represents difference in phase components. The phase only correlation between two images $I_1(x, y)$ and $I_2(x, y)$ is computed from the inverse 2-D DFT of $R_{D_1D_2}(k_1, k_2)$ as in the following.

$$r_{I_1I_2}(x, y) = \frac{1}{NM} \sum_{k_1k_2} R_{D_1D_2}(k_1, k_2) e^{i2\pi x k_1/N} e^{i2\pi y k_2/M} \quad (9)$$

The similarity between two normalized finger knuckle images, using the band limited phase only correlation, is computed from (9) by limiting k_1 and k_2 to some limit instead to N and M respectively. The maximum value of band limited phase only correlation in (9) is normalized to one.

4. Combining Minor and Major Finger Knuckles

Multiple pieces of evidences from the same finger dorsal image, *i.e.*, major and minor knuckle patterns, can be simultaneously combined to improve matching accuracy for the personal identification. Among several possibilities to integrate *minor* and major knuckle patterns, this

work explored match score[§] combination using linear and nonlinear strategies. In current application, it is important to select the score level combination strategy which is computationally simpler and yet effective to significantly improve the performance. Therefore several popular approaches were explored to consolidated matching scores (s_c) from the simultaneously extracted major and minor finger knuckle images, and these are summarized in the following.

Max: $$s_c = \max_{\forall s_{minor}, s_{major}}\left(s_{minor}, s_{major}\right) \quad (10)$$

Product: $$s_c = s_{minor} * s_{major} \quad \forall s_{minor}, s_{major} \quad (11)$$

Weighted Sum: $$s_c = s_{minor} * (w) + s_{major} * (1 - w), \quad \forall s_{minor}, s_{major} \quad 0 \leq w \leq 1 \quad (12)$$

Nonlinear: $$s_c = \left(\frac{1+s_{minor}}{1+s_{major}}\right)^{\gamma} * \left(1 + s_{major}\right)^2 \quad (13)$$

where s_{major} and s_{minor} represents the matching scores from the major and minor finger knuckle images respectively. The nonlinear fusion approach has shown to achieve best performance in [5] and was therefore also evaluated in the experiments.

In this work, a holistic approach to combine major and minor knuckle pattern matching scores was also investigated. Such an approach dynamically combines two matching scores using holistic rule of combination and can be described as in the following [5]:

$$s_c = \left\{(s_{major} * \tau) + (s_{minor} * (1 - \tau))\right\} * \left(1 + \frac{1}{2 - s_{major}}\right) \quad (14)$$

This score level combination scheme can generate consolidated matching scores which follow the trends which are similar to the dominant knuckle patterns, *i.e.*, when the matching score from minor knuckle patterns are high, their combined scores will also become higher and vice versa. The controlling factor τ reflects the reliability of knuckle pattern match scores and is chosen during the training phase. In this work the matching scores from the major finger knuckle are

[§] Match score level combination can allow each of the match observation to operate independently and has emerged as the most preferred method in the multibiometrics literature[18], [30]

chosen as the controlling factor to benefit from their superior accuracy due to its rich/stable knuckle patterns.

Matching using Cohort Information

In the conventional score-level multibiometrics decision making process, the combined matching score is compared with a predetermined decision threshold. The unknown user identity corresponding to the combined matching score is assigned to the imposter class if the combined matching score is more than or equal to the decision threshold. The selection of decision threshold determines the operating point of a biometrics system and is largely based on the nature of application [30]. The distribution of matching scores from the cohort users can be used to more accurately ascertain the likelihood that an unknown user belongs to the genuine or imposter class. Therefore the performance from the combined matching scores, generated using the major and minor finger knuckles, can be further improved by employing the cohort information in the decision making process [18]. The consolidation of authentication decisions, from such combined knuckle matching scores using the cohort information is achieved as follows: I Firstly compared the combined matching score obtained from an unknown user with the given decision threshold, say *T*. If the combined genuine score is less than a decision threshold *T*, the unknown user identity corresponding to the combined matching score is assigned to the genuine class. However this user is not immediately rejected or assigned to the imposter class if his/her combined matching score is more than decision threshold *T*. Instead, we can employ cohort information to further decide if there is still some likelihood that this particular user can belong to the genuine class. If the combined matching score corresponding to this user is still smaller than all the corresponding cohort matching scores, then the user is still assigned to the genuine class. However, if the combined matching score is equal to or more than the corresponding cohort matching scores then the user is assigned to imposter class. The consolidation of decisions using such cohort information requires additional comparisons with the cohort matching scores *whenever* the combined matching score is higher than the decision

threshold. Therefore the usage of cohort information in decision making can increase the computational complexity in decision making. However, such added computations can be justified by the significant performance improvement, as can be observed from the experimental results presented in the next section.

5. Experiments and Results

The experiments were performed in two phases to ascertain the usefulness of *minor* finger knuckle patterns for the biometric authentication. Firstly, the database of 250 *middle* finger dorsal images acquired from 50 subjects was utilized to ascertain the superiority of four matchers considered in this work. The finger dorsal imaging setup is same as employed in [26]. The images were acquired in the outdoor and also in the indoor environment from male/female volunteers in the age group of 4-60 years. The performance evaluation is achieved by 5-fold cross-validation and the average of the experimental results is reported. This approach can represent more realistic experiments [6]-[7] as the knuckle images have high variations within the same class which can be attributed to shadows, illumination, scale, pose variations which also limit the segmentation accuracy.

Each of the finger dorsal images were employed to automatically segment *minor* finger knuckle images of 160 × 180 pixels using the approach detailed in section 3. Although the focus of this work is on the *minor* finger knuckle identification, major finger knuckle images of 160 × 180 pixels size were also automatically segmented for the comparison and performance improvement. The algorithm for the automated segmentation of major finger knuckle is quite similar to as developed in [3], [7] but also utilizes the key results from the minor finger knuckle segmentation (section 3).

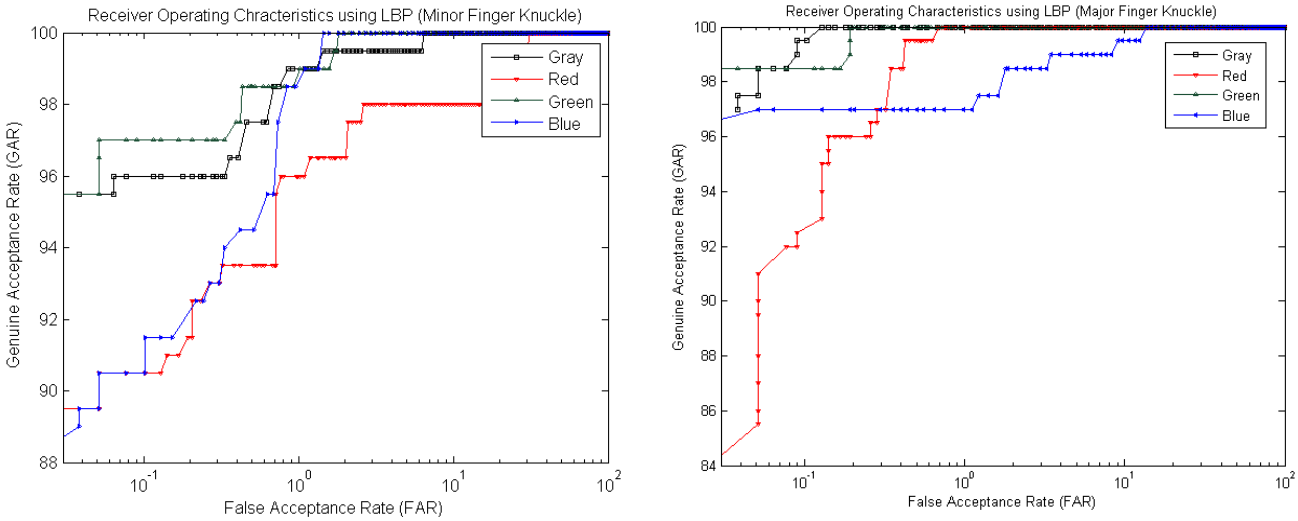
The *minor* finger knuckle segmentation algorithm developed in this paper achieves quite promising segmentation results. However the stability of the segmented region may vary among the finger dorsal images, even from the same subject, and this can be attributed to the absence of

user-pegs or constraints for the finger movement between successive imaging. The limiting stability of segmented region is a reasonable tradeoff** for the enhanced user convenience during the imaging. The accuracy of the minor finger knuckle segmentation is jointly evaluated from the useful matching accuracy that can be achieved from the experiments.

In order to ascertain any possible advantage of using any specific color channel, the experiments were also performed for red (R), green (G), blue (B) channel images, along with their gray level images. The experimental results from the database of 50 subjects is summarized in table 1, with their respective receiver operating characteristics (ROC) shown in figure 5-6.

Table 1: Comparative Experimental Results using Equal Error Rate (EER).

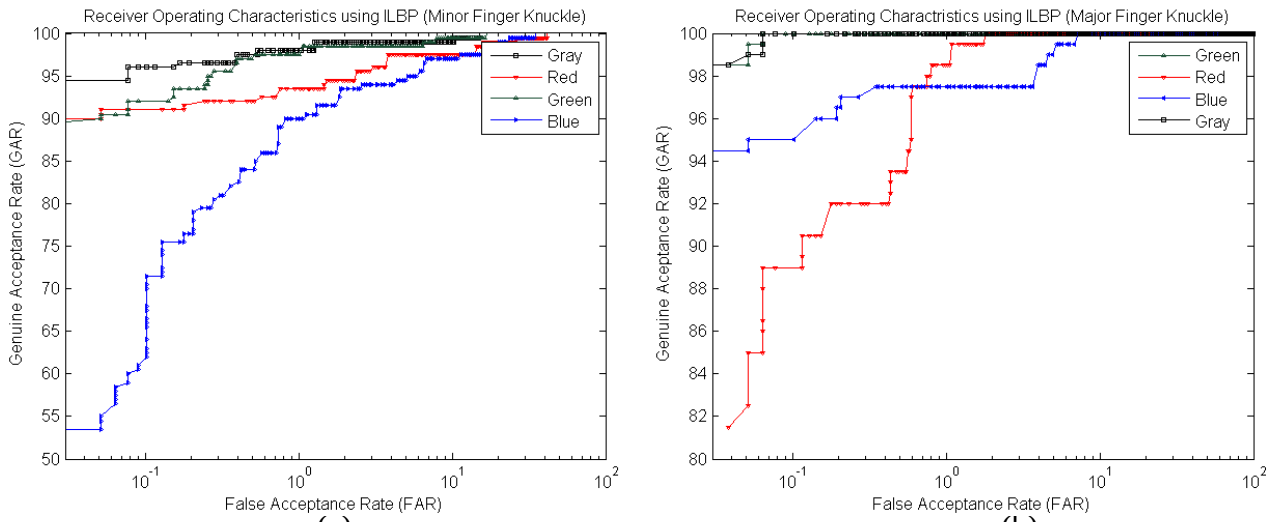
	Local Binary Pattern				*Improved Local Binary Pattern*				*1D Log-Gabor*	*BLPOC*
	Red	Green	Blue	Gray	Red	Green	Blue	Gray	Gray	Gray
Minor Knuckle	2.5%	1.01%	1.08%	1.0%	3.7%	1.5%	5.12%	1.25%	0.5%	0.3
Major Knuckle	0.5%	0.2%	1.75%	0.12%	1.27%	0.6%	2.5%	0.6%	0.09%	0



(a) (b)

Figure 5: Receiver operating characteristics using LBP matcher from automatically segmented (a) *minor* finger knuckle images and (b) major finger knuckle images.

** Employed finger dorsal imaging setup is more realistic to evaluate the key motivation of *simultaneous finger knuckle matching* from the operational slap fingerprint devices at border-crossings (*e.g.* US VIST programme [31]).

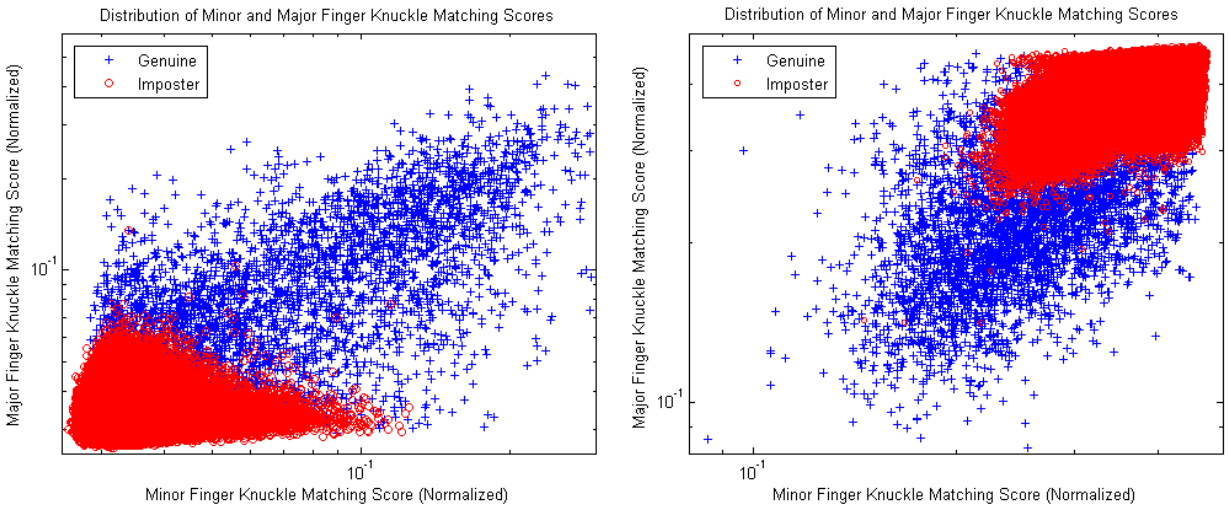


(a) (b)

Figure 6: Receiver operating characteristics using ILBP matcher from automatically segmented (a) *minor* finger knuckle images and (b) major finger knuckle images.

These experimental results could not establish superiority of any specific color channel and therefore gray scale representation was judicious choice for further experiments/use. The experimental results in table 1 suggest that *minor* finger knuckle images can also be accurately matched if utilized individually. However as expected, the accuracy from the corresponding major finger knuckle images is superior. The experimental results also suggest that matching finger knuckle images using BLPOC and 1-D log-Gabor filter based approach can achieve superior results than those using LBP or ILBP, based approach considered in this work. Therefore comparative performance for the verification problem using *minor* and/or major finger knuckle was further investigated on the full finger knuckle database from 503 subjects using two best performing matchers (BLPOC and log-Gabor) from previous experiments. In order to ascertain the performance from the investigated approach using minimum (one) training image and also using four training image, the experimental results are reported using two test protocols. The test *protocol A* (all-to-all) reports average of performance when every finger knuckle image from every subject in the database is used as respective training image/sample. The test *protocol B* generates average of five tests where each of the five images from each of the subjects are used as the *test images* while remaining other images from the respective subjects are used as *training images*. In each of the verification experiments, we report average of experimental results using equal error rate (EER) and receiver operating characteristics (ROC). The protocol B with five

tests generated 2515 (503 × 5) genuine comparisons and 1262530 (502 × 503 × 5) imposter comparisons while protocol A generated 5030 genuine comparisons and 3156325 imposter comparisons using protocol A. Figure 7 shows the distribution of genuine and imposter matching scores from two simultaneously extracted major and minor finger knuckle images. The score distribution shown in this figure suggests that the combination of major and minor finger knuckle scores can be explored to improve matching accuracy. The match score combination of major and minor knuckle scores employed $\tau = 0.6$ for the holistic fusion and $\gamma = 1.4$ for the nonlinear fusion. All the match scores from the major knuckle using log-Gabor filter are normalized (scaled-up) before their combination with corresponding minor knuckle match scores. The cohort matching results presented in this paper employed the combined matching scores from the score level fusion scheme (among five) that achieved the best results. The *max* rule using the 1-D log-Gabor filter based approach is essentially using minimum of matching distance from two knuckle images (maximum similarity score) since Hamming distance is used as distance metric.



(a) (b)

Figure 7: Distribution of matching scores from (a) BLPOC and (b) log-Gabor filter based approach using protocol A.

Band Limited Phase Only Correlation

The ROC from minor and major finger knuckle matching using BLPOC matcher (section 3) is shown in figure 8. Figure 9 illustrates the ROC using combination of simultaneously extracted

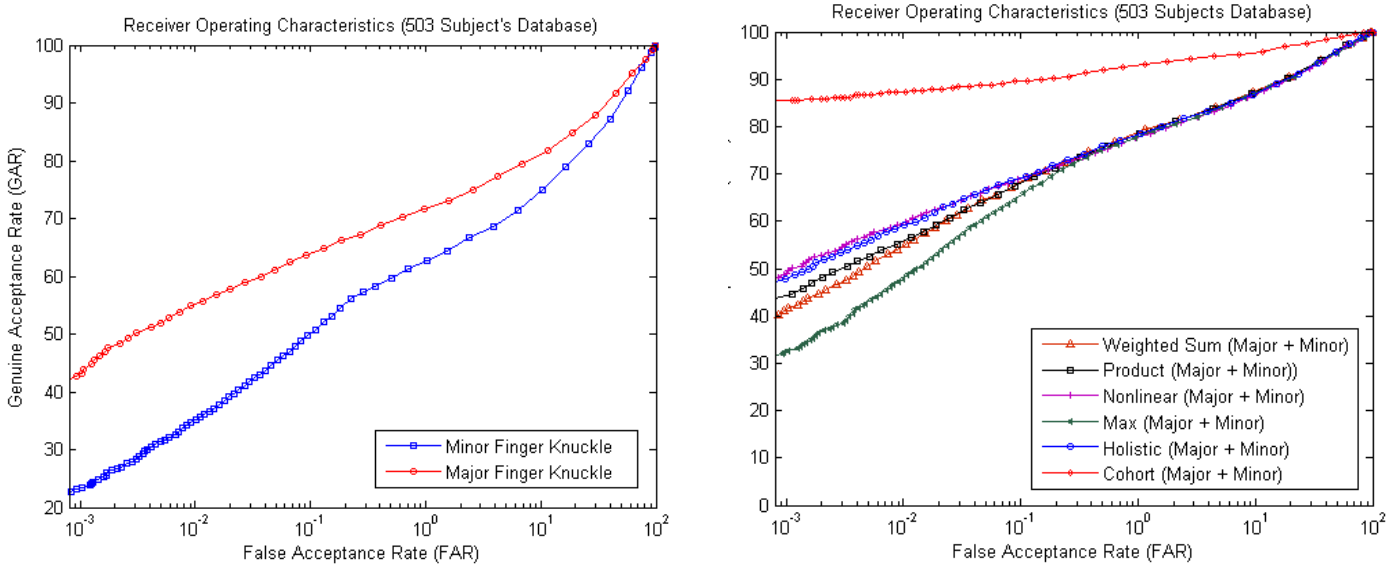


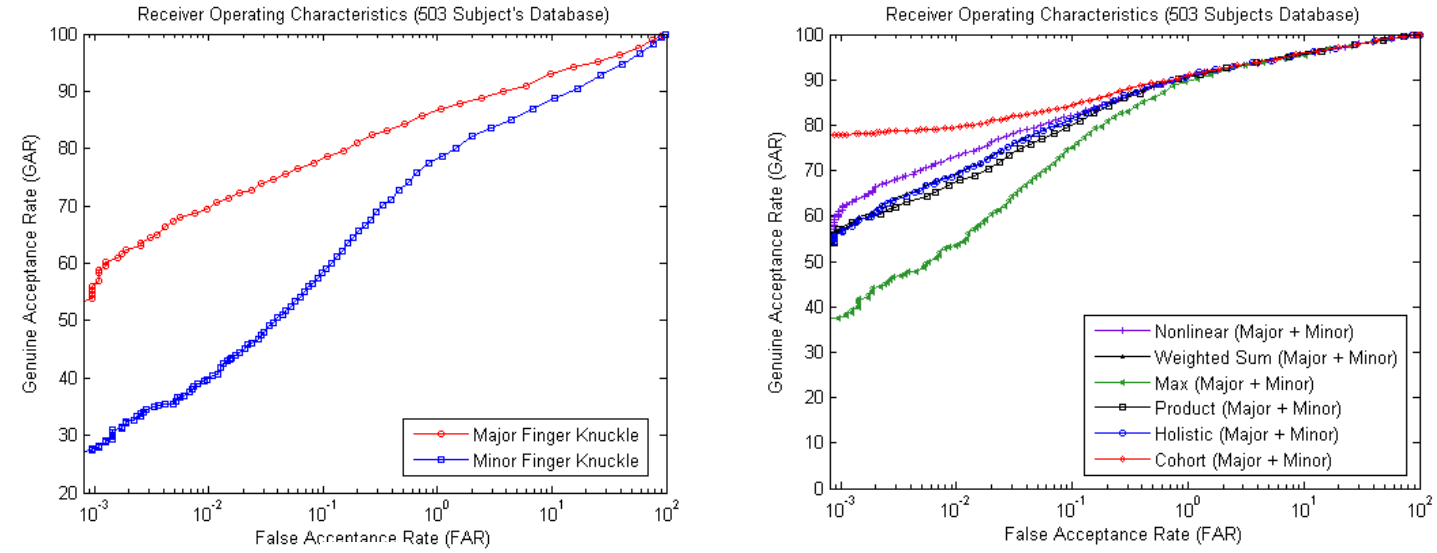
Figure 8: (a) The ROC from *protocol A* using BLPOC based matching, and (b) performance using match score combination using various schemes considered in this work.

Table 2: Comparative Performance using *EER* and *DI* (Protocol A).

Knuckle Pattern(s)	*Equal Error Rate (%)*	*Decidability Index*
Minor Finger Knuckle	19.81	0.7961
Major Finger Knuckle	16.27	0.8279
Holistic	11.95	0.8663
Nonlinear	12.33	0.8379
Weighted Sum	11.97	0.8779
Max	12.15	0.9267
Product	12.03	0.8611
Cohort Combination	5.12	0.8663

Table 3: Comparative Performance using *EER* and *DI* (Protocol B).

Knuckle Pattern(s)	*Equal Error Rate (%)*	*Decidability Index*
Minor Finger Knuckle	11.12	0.972
Major Finger Knuckle	7.973	1.000
Holistic	5.59	1.035
Nonlinear	5.66	0.994
Weighted Sum	5.53	1.054
Max	9.43	1.084
Product	5.52	1.046
Cohort Combination	5.5	1.035



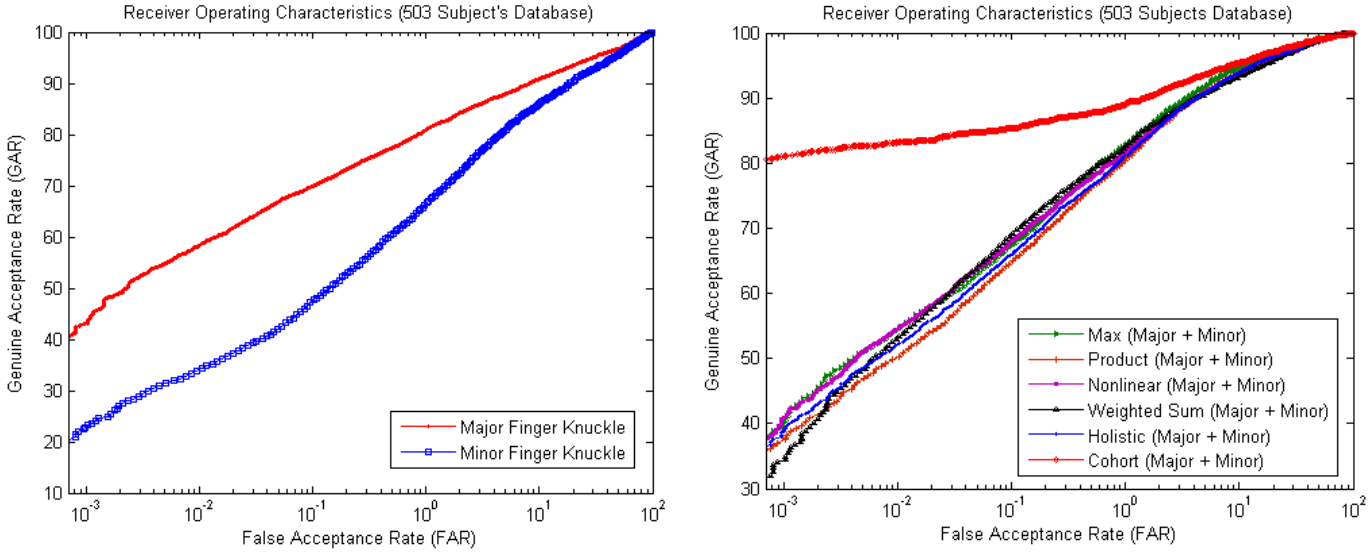
(a) (b)

Figure 9: (a) The ROC from *protocol B* using BLPOC based matching, and (b) performance using match score combination using various schemes considered in this work

minor and major knuckle images using various score level combination strategies introduced in section 4. Table 2 illustrates corresponding EER and the decidability index (*DI*) [32]. It can be observed from the ROC in figure 8(b)-9(b) that the score level combination of minor and minor knuckle matching score be successfully employed to improve the matching performance. The experimental results also consistently suggest superiority (especially at lower FAR) of cohort matching strategy to significantly improve the performance. It may be noted that the usage of cohort information does not alter distribution of genuine or imposter matching scores. Therefore the decidability index remains unaltered from the combined knuckle matching using the cohort information. The individual performance using minor and major finger knuckle shown for *protocol B* (figure 9, table 3) is superior than those from *protocol A* (figure 8, table 2), which is quite expected as *protocol B* uses large number of intra-class images during the matching.

1-D Log-Gabor Filters

The experimental results using 1-D log-Gabor filter based matcher is shown in figure 10-11. Table 4-5 shows corresponding EER and DI scores from the respective experiments in figure 10-11. It can be observed that 1-D log-Gabor based filter based approach, both for minor and major



(a) (b)

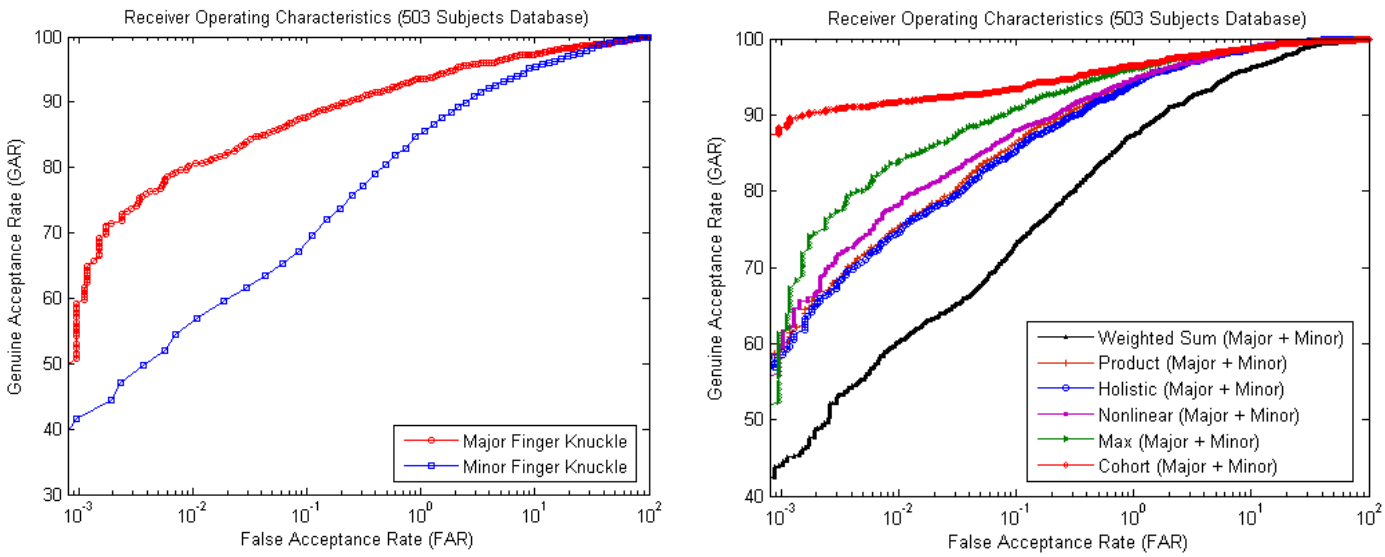
Figure 10: (a) The ROC from *protocol A* using log-Gabor filter based matching, and (b) the performance using various match score combination schemes considered in this work.

Table 4: Comparative Performance using *EER* and *DI* (Protocol A).

Knuckle Pattern(s)	*Equal Error Rate (%)*	*Decidability Index*
Minor Finger Knuckle	12.605	1.6543
Major Finger Knuckle	9.4085	1.8211
Holistic	7.402	2.021
Nonlinear	7.55	2.0354
Weighted	7.61	1.9802
Max	6.734	2.178
Product	7.305	2.0115
Cohort Combination	5.92	2.021

Table 5: Comparative Performance using *EER* and *DI* (Protocol B).

Knuckle Pattern(s)	*Equal Error Rate (%)*	*Decidability Index*
Minor Finger Knuckle	6.32	2.4353
Major Finger Knuckle	3.94	2.7401
Holistic	3.045	3.047
Nonlinear	3.01	3.104
Weighted Sum	5.497	2.5596
Max	2.535	3.0782
Product	2.89	3.0293
Cohort Combination	2.48	3.0782



(a) (b)

Figure 11: (a) The ROC from *protocol B* using log-Gabor filter based matching, and (b) the performance using various match score combination schemes considered in this work.

finger knuckle images, achieves superior performance than those using BLPOC matcher. The combination of matching scores using holistic fusion can significantly improve the performance, similar to as shown in figure 8-9 using BLPOC matcher. The experimental results presented in figure 8-11 indicate the advantage and benefits of simultaneously extracting *minor* finger knuckle images for significantly improving (major) finger knuckle matching performance.

The BLPOC matcher, as described in section 3, uses correlation of spectral features which are quite different than those extracted using the matcher based on log-Gabor filter or using *KnuckleCodes* as in [7]. Recently the BLPOC based matcher has also shown to outperform several other competing methods in [34] and was therefore judiciously selected for the performance evaluation for minor (also major) finger knuckle matching. The experiments were also performed to ascertain performance using the *KnuckleCode* matcher described in [7]. However, the performance achieved (EER of 11.66% and 8.07% respectively for the minor and major finger knuckle matching using protocol B) was not competing or superior with those shown in table 5 using log-Gabor based approach. The *KnuckleCode* based encoding scheme however requires least computations to generate knuckle templates, as compared to log-Gabor or BLPOC based matcher, and could be advantageous in online applications.

It is useful to ascertain plausible reason why the log-Gabor filter based knuckle matcher can achieve superior performance than using *KnuckleCodes* in [7]. It may be noted that *KnuckleCodes*, similar to RLOC [35], encodes each of the knuckle features into eight level codes. Therefore *KnuckleCode* features are expected to be more discriminant, as compared to the case when same features are encoded using log-Gabor filter into binary (two-level) codes, but more sensitive to noise or imaging variations which are common during contactless imaging as used in this work. It may not be to therefore statistically argue that the likelihood of mismatching multilevel *KnuckleCodes* is expected to be higher than using binarized codes resulting from the log-Gabor filters.

6. Stability of Finger Knuckle Patterns

Several research publications [18], [22] have identified ubiquity and uniqueness as essential properties for any new physiological pattern to serve as new biometric. The experimental results presented in previous section have attempted to ascertain uniqueness of finger knuckle patterns, using the largest database to-date (over 500 subjects), with encouraging results. The ISO/IEC

2382-37 [20] standard requires that any potential 'biometric characteristic' should be able to ensure 'repeatable biometric features' to be able to serve as useful biometric. In this context, the earlier studies on finger knuckle biometrics used images that were collected from individuals in two occasions. However the interval between these two sessions was quite small, 4-6 weeks in [3] or 3-4 weeks in [11], and may not be adequate to reasonably indicate stability of knuckle pattern characteristics to serve as reliable biometric, especially for forensic applications where the time interval for matching the suspects could be years. Lack of any study on same person-specific variations can be attributed to the fact that the use of finger knuckle patterns have recently emerged [1], [3] in biometrics investigations as a potential trait and the fact that frequent/long-term data is expensive and difficult to sustain.

In order to ascertain the finger knuckle stability, the finger dorsal images from different subjects after the interval of more than 5 years were acquired[††] and some of these images are reproduced in figure 12. This figure shows image samples from middle finger dorsal images from adults of (a) 59 years, (c) 36 years, (e) 37 years, and (g) 25 years age when the first image samples were acquired. Their corresponding knuckle images after an interval of more than 5 years are also shown in this figure. It can be observed that the shape of key creases and lines in the minor and major knuckle patterns are highly stable in these sets of images from adults of varying age group. Figure 13 and 14 shows another set of middle finger dorsal images from two children acquired in 2007 at the age of 7 years and 9 years respectively. Their corresponding images acquired after more than 6 years (2013) are also shown in this figure. The shape of major creases in two sets of images is observed to be quite stable.

[††] The purpose of this study is not to ascertain template aging [28], which is true/useful for more established or matured biometric, but to investigate on the stability of knuckle patterns for its possible use in civilian and forensic applications.

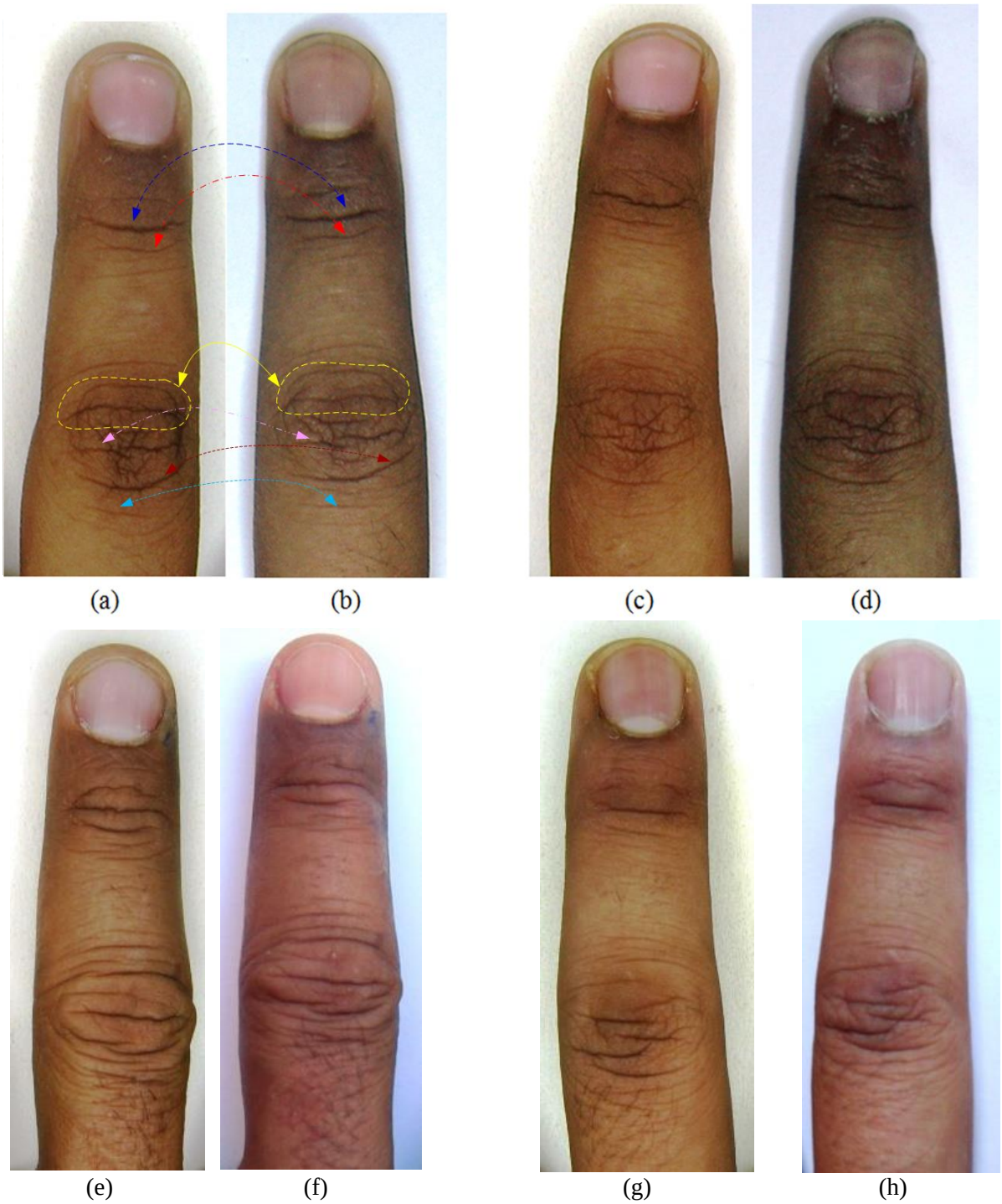
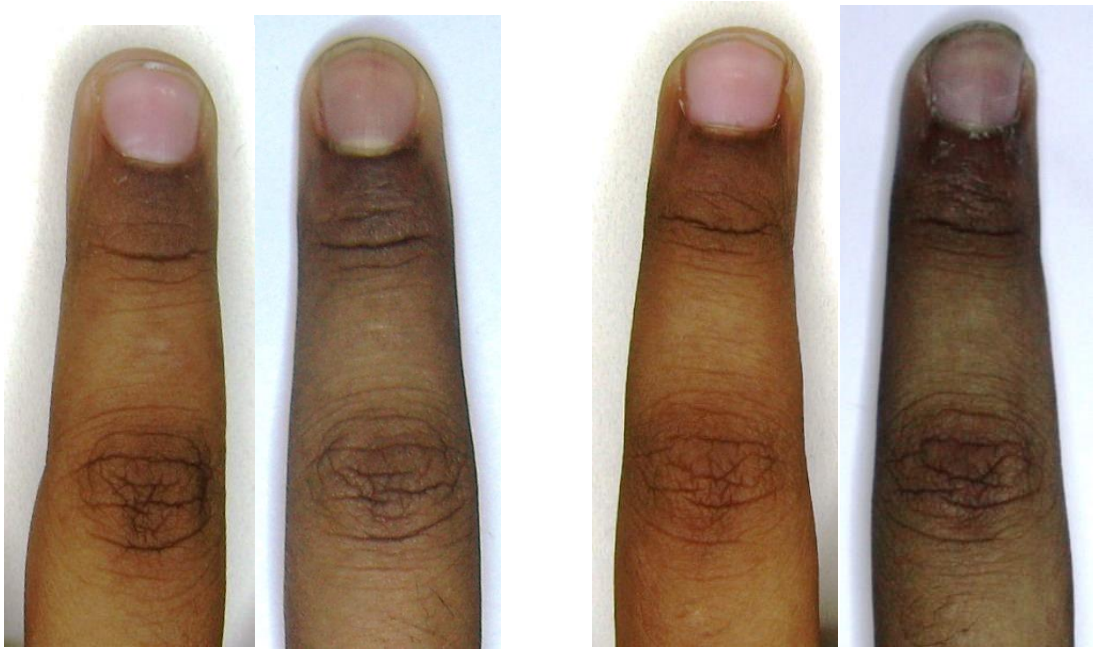
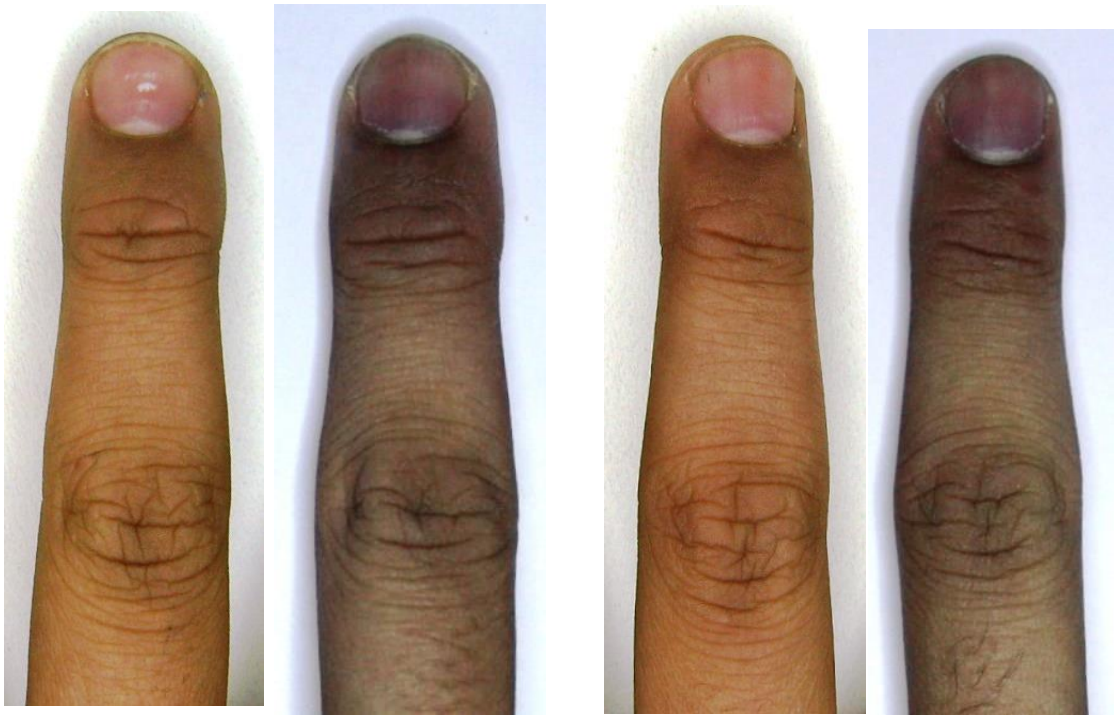


Figure 12: Middle finger dorsal images with knuckle patterns from four different subjects. Images in (a) were acquired in 2006 in *indoor* environment while images in (b) were acquired in 2012/13 in *outdoor* environment. The variation in imaging distance and environment has also introduced.



(a) (b) (c) (d)

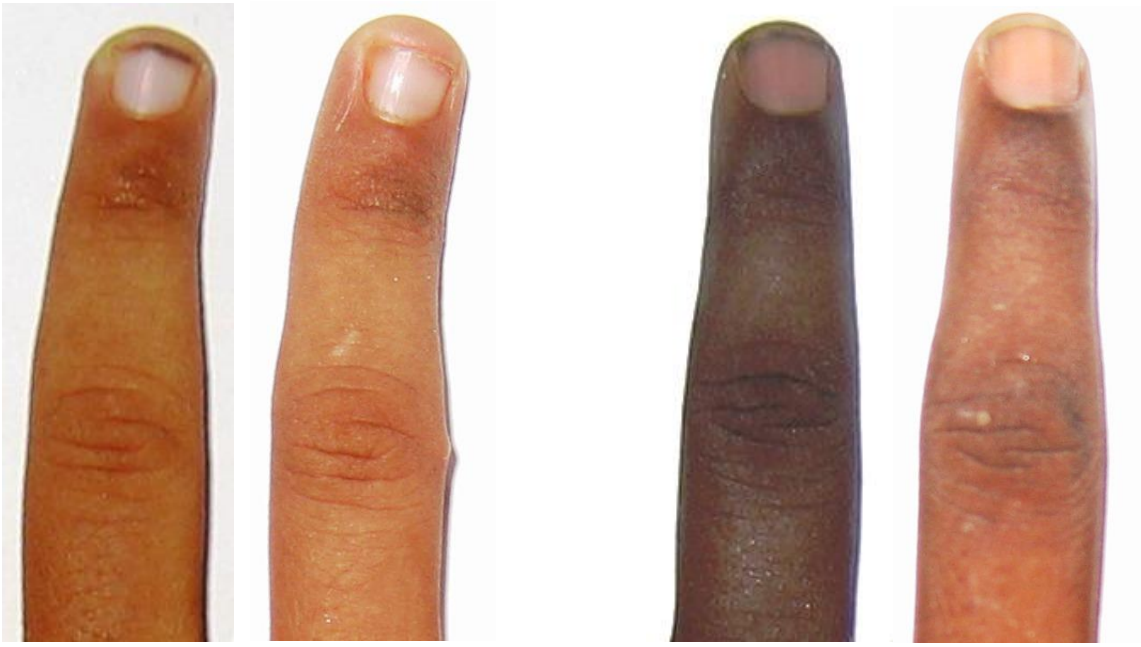
Figure 13: Middle finger dorsal images with knuckle patterns from a seven year old child. The images in (a) and (c) are from right and left hand respectively, and were acquired in indoor environment. The images in (b) and (d) were acquired after 6 years, from the same child aged 13 years, in outdoor environment from same fingers using contactless imaging.



(a) (b) (c) (d)

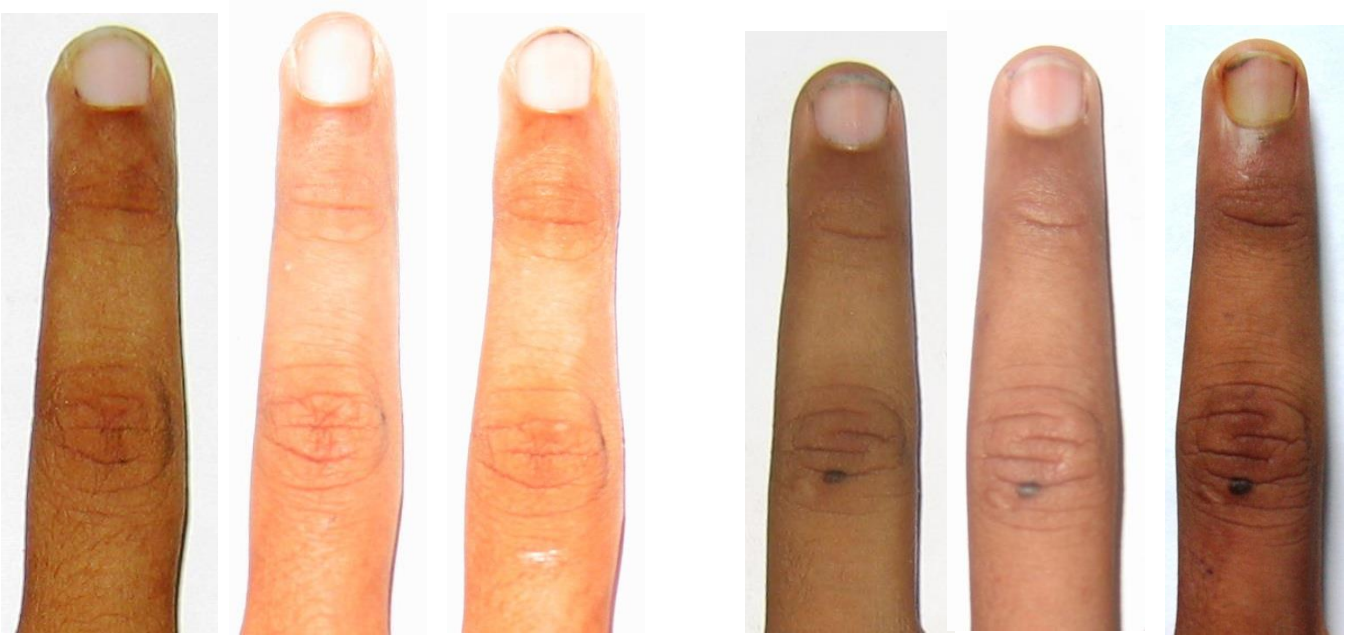
Figure 14: Middle finger dorsal images with knuckle patterns from a nine year old child. The images in (a) and (c) are from right and left hand respectively, and were acquired in indoor environment. The images in (b) and (d) were acquired after 6 years, from the same child aged 15 years, in outdoor environment from same fingers using contactless imaging.

The images in figure 15 and 16 can be used to ascertain the stability of finger knuckle patterns over four year period for children's experiencing high physiological growth. These sets of images were acquired in outdoor environment and do have some noise. The images from 4 year old children's in figure 11, and their corresponding images at the age of 8 years, suggest that the shape of crease patterns in major and minor knuckle are quite stable. However some of these creases can be observed to be further extended in these images. Such enrichment of creases or changes in pigmentation can be attributed to the physiological growth in children's under the period of imaging. Similar observations can also be observed from the set of images from 10 years old children in figure 16. Figure 17 shows another set of images from two females of 13and 14 year's old and corresponding images acquired over a period of four years. Careful visual inspection of these images (and others) in the database acquired point towards high degree of stability in the curved creases and lines forming major/minor knuckle patterns. Therefore study of finger knuckle patterns require further attention especially from the researchers/scientists grappling with image forensics and surveillance problems.



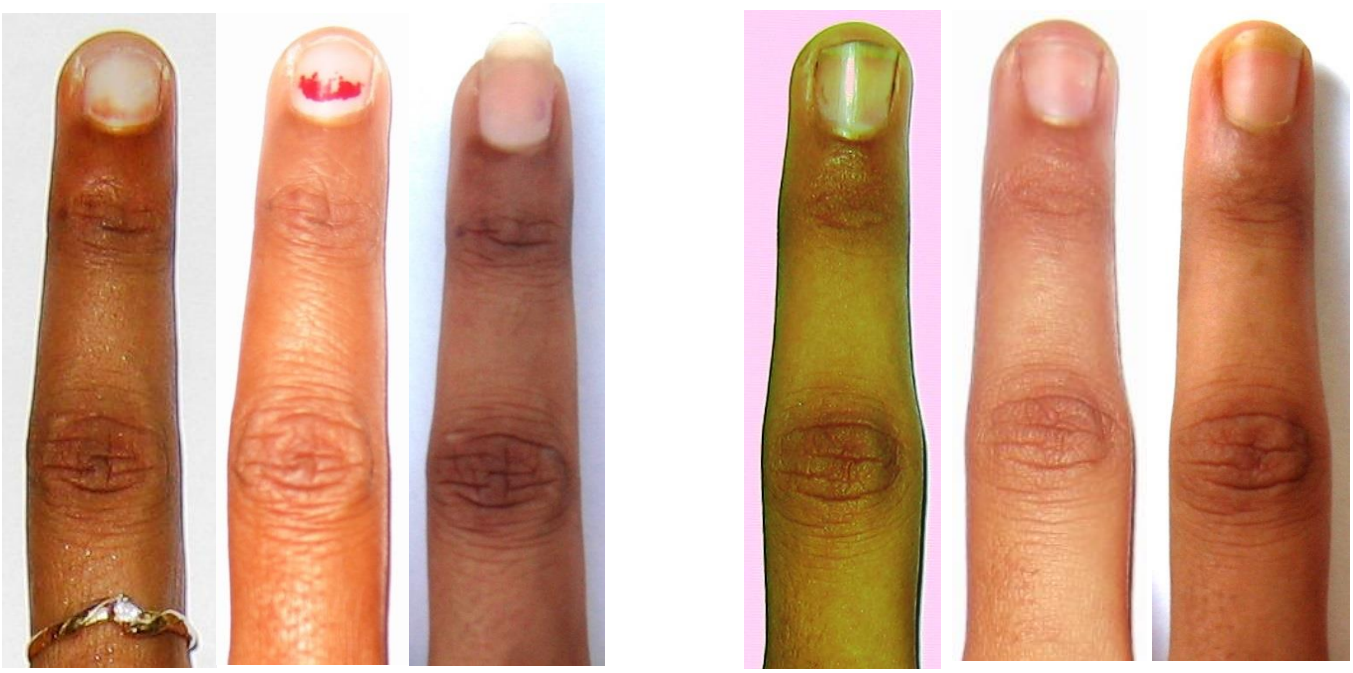
(a) (b) (c) (d)

Figure 15: Middle finger dorsal image of two children aged ~ 4 years in (a) and (c), corresponding images when they are about 8 years old in (b) and (d) respectively.



(a) (b) (c) (d) (e) (f)

Figure 16: Middle finger dorsal image of a volunteer of ~ 10 years in (a); image after interval of about 2 years in (b), and image acquired after 4+ years interval in (c); another volunteer at the age of ~ 13 year in (d), at the age of ~15 years in (e), at the age of ~17 years in (f).



(a) (b) (c) (d) (e) (f)

Figure 17: Middle finger dorsal image of from two *female* volunteers aged ~ 14 years in (a) ~13 years in (d); corresponding images after an interval of ~ 2 years in (b), (e), and after an interval of ~4+ years in (c), (f) respectively.

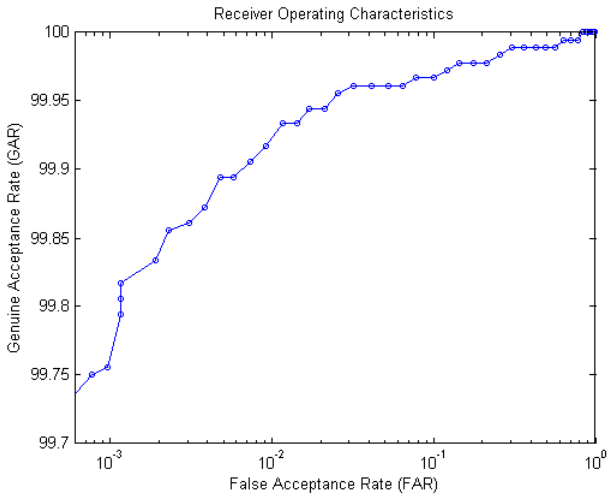


Figure 18: The ROC from matching two session finger knuckle images acquired after time-lag of 4-7 years.

The stability of finger knuckle patterns can also be ascertained by matching images acquired after very long interval using the feature extraction and matching approach discussed in section 3. Such matching results from matching two session database of finger knuckle images from 30 client fingers are shown in figure 14. The finger knuckle images acquired in first session for the corresponding clients were used as the registration or training images while the images acquired after very long interval from the second session imaging were used to ascertain the performance. The minimum time lag between two sessions was 4 years while the maximum interval between two sessions was 7 years. The verification accuracy between two session images is quite promising (EER of 3.62%) and can be ascertained from ROC in figure 18. It should be underlined that error rates shown/achieved from the experiments includes error caused due to strong changes in the environment, camera, or user behavior during contactless finger imaging, rather than just due to changes in source biometric/knuckle patterns.

7. Conclusions and Further Work

This paper has successfully investigated the possibility of employing *minor* finger knuckle images for the biometric identification. The coarse-to-fine segmentation strategy developed in this paper has been quite successful as it has been able to achieve higher matching accuracy. The experimental results illustrated in this paper, on the database of 503 subjects, can achieve promising performance (EER of 6.29% and 12.6% under two protocols) from only using contactless *minor* finger knuckle images. The experimental results reported in this paper also suggest that the simultaneous use of major and *minor* finger knuckle images can help to

significantly improve the performance that may not be possible by using either *minor* or major finger knuckle images alone.

Two finger joints, *i.e.*, MCP and DIP joint as shown in figure 2, have significant backward motion and therefore require some mechanism to prevent dislocation and subluxation. Such mechanism is anatomically built in fingers and consists of combination of bony restraints, ligaments, extensor tendinous attachments and biomechanical action of muscles. *Therefore the knuckle patterns, which are formed due to stress or folding pattern of* (additional) *dorsal skin at MCP and DIP joints, closely reflect anatomy of his/her fingers*. This paper has also detailed a preliminary but first promising attempt to ascertain stability of finger knuckle patterns. However the use of only major knuckle patterns, small number of subjects, and lack of systematic evaluation in various age groups reflects narrow focus on this topic in this paper. Availability of such images [21] acquired after an interval of 4-7 years in public domain will serve as useful evidence to favorably argue on suspects/offenders for forensic and law-enforcement applications.

The finger dorsal images employed this paper were acquired in single session and therefore conclusions on the accuracy points towards the uniqueness of major/minor finger knuckle patterns in the given database rather than on the stability of such patterns with time. Prior efforts in the literature [3], [10]-[11] have shown the stability of major finger knuckle features by employing two session database, in an interval of 4-6 weeks, to ascertain the stability their stability in respective duration. Lack of any long interval study on the stability and individuality of finger knuckle patterns has cautioned the use of finger knuckle images for any commercial applications and therefore there is pressing need for systematic/scientific study in this area. Accurate segmentation of stable major and *minor* finger knuckle regions is significantly important as it can control the achievable identification accuracy from the finger dorsal images. Therefore further efforts are required to develop accurate segmentation algorithms which can also address common imaging challenges from less-constrained finger imaging, *i.e.*, off-axis view, poor contrast, motion blur, defocusing, over-saturation, and occlusion. Individual error

rates, *i.e.*, from minor or major finger knuckle images, achieved from the experimental results are still high to be comparable from those possible using the well-established modalities like fingerprints. This can be attributed to the use of database from a large number of subjects (503), under varying imaging conditions [33] (indoor and also outdoor environment) and more importantly to the use of contactless imaging which generally produces large intra-class variations. The log-Gabor based approach employed in this paper generates binary features that are similar or same as the *IrisCodes* pursued in [32]. Therefore the experimental results and analysis essentially argues superiority of *IrisCodes* over other competing methods developed in the literature (like *KnuckleCodes*, RLOC, OrdinalCodes [36], *etc*.). Such an argument requires further statistical analysis and experimental results in the further work. *Although much more work remains to be done, the results presented in this paper indicate that the human identification using 'minor' finger knuckle images can constitute a promising addition to the biometrics security, especially for image forensics and surveillance applications.*

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