Can We Use *Minor* Finger Knuckle Images to Identify Humans?

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***Abstract*—Biometric identification using finger knuckle imaging has generated lot of promises with interesting applications in forensics and remote 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' or 'upper' finger knuckle patterns can either be used as independent biometric patterns or employed to improve the performance from the major finger knuckle patterns. This paper investigates a completely automated approach for the 'minor' finger knuckle identification by developing steps of region of interest segmentation, image normalization, enhancement and robust matching to accommodate image variations. Comparative experimental results are presented for matching the normalized 'minor' finger knuckle images using LBP, ILBP and 1D log Gabor filter. The efforts to develop automated 'minor' finger knuckle patterns achieve promising results, with 1.04% equal error rate on the database of 202 subjects, and illustrate its simultaneous use to improve the performance for conventional finger knuckle identification.**

I. Introduction

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

A normal human 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 1 from a typical finger dorsal image used in this work. 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.

A. Related Work and Motivation

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.

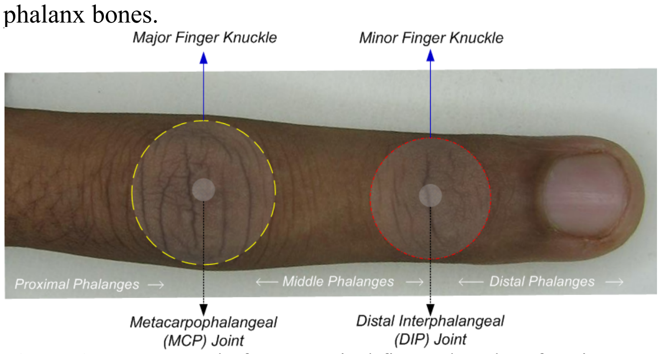

Figure 1: Image sample from a typical finger dorsal surface image identifying the *major* and *minor* knuckle pattern regions with respect to the MCP/DIP joints.

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

† 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].

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joining distal phalanx and middle phalanx bones and can also be quite distinctive for biometrics identification. This paper has attempted to examine biometric identification capability for humans using such *minor* finger knuckle images and has developed effective algorithms for the automated segmentation of region of interest, image normalization, enhancement and robust matching to accommodate inherent image variations. These steps are detailed in the following sections.

II. Knuckle Image Segmentation and Normalization

Accurate biometric identification of humans using *minor* finger knuckle patterns requires robust segmentation and normalization of region of interest images. 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 2 illustrates simplified block diagram for the finger knuckle segmentation strategy attempted in this work to segment fixed size *minor* finger knuckle images.

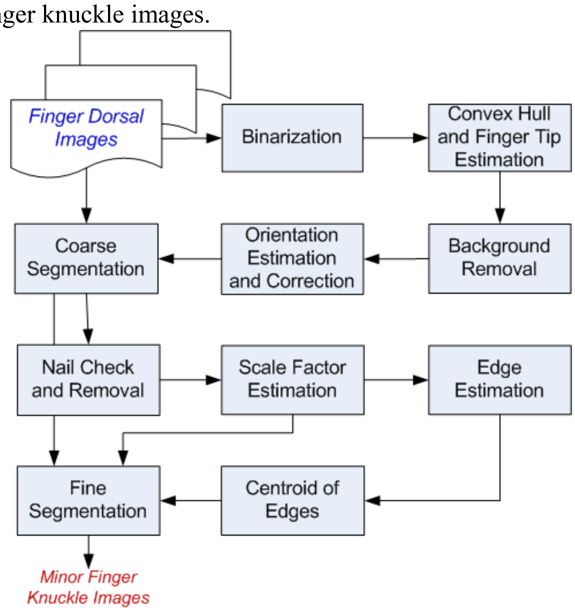


Figure 2: Simplified block diagram illustrating key steps in the automated segmentation of *minor* finger knuckle images from the finger dorsal images

Each of the acquired finger dorsal images is firstly subjected to binarization using Otsu's thresholding. The resulting images are cleaned by removing 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 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 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

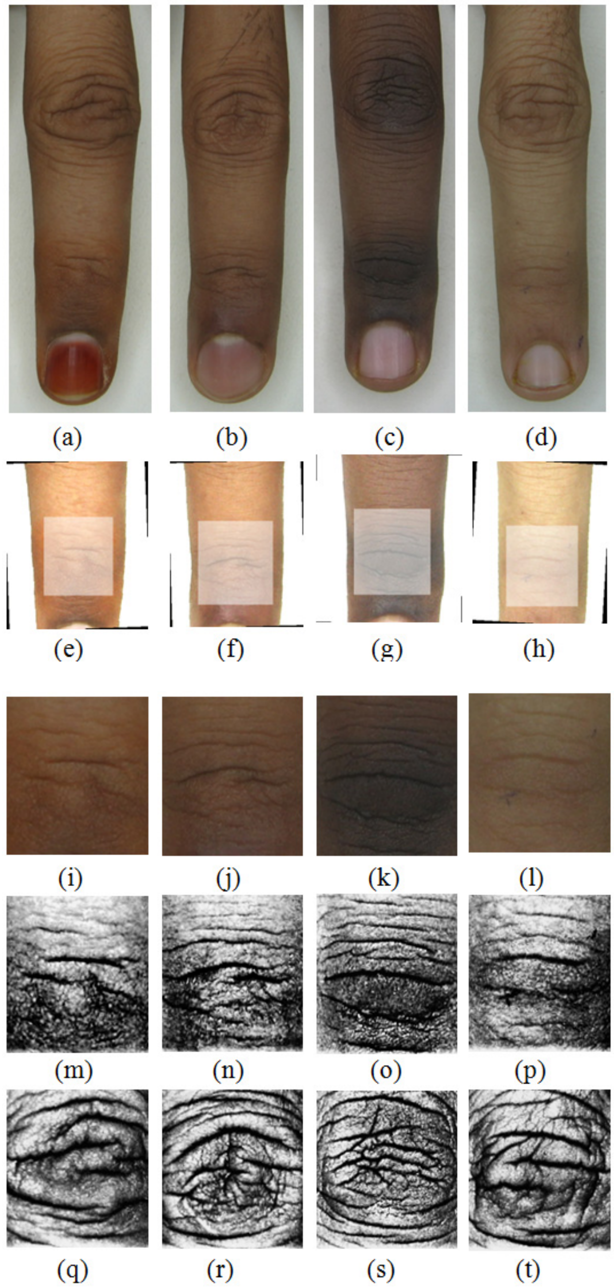


Figure 3: Finger dorsal images in (a)-(d), corresponding *minor* finger knuckle region identified for segmentation during fine segmentation in (e)-(h), segmented *minor* finger knuckle images in (i)-(l), images after enhancement in (m)-(p), respective segmented and enhanced major finger knuckle images in (q)-(t).

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.

A. Image Enhancement

The finger dorsal surface is 3D curved surface and such curves can result in uneven illumination reflections and shadows. Therefore the segmented 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 in [7] which firstly estimates the average background illumination in the 16 × 16 pixels sub-blocks. The estimated illumination is then subtracted from the original image to remove the uneven illumination. The resulting image is then subjected to the histogram equalization operation which generates enhanced minor finger knuckle image for the feature extraction. Figures 3 (m)-(p) shows image samples after the image enhancement operations.

III. 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 match minor/major finger knuckle images. The experimental results in this paper have employed Local Binary Patterns [12], Improved Local Binary Patterns [13] and 1D Log-Gabor filter based matchers [14]-[15] for the performance evaluation. These matchers are briefly summarized in the following.

A. Local Binary Patterns

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 [2]:

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

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

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

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:

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

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..

B. 1D Log-Gabor Filters

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

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

where ω_0 is the central frequency, φ_0 is the orientation, σ_f and σ_φ are the constants that determine radial and angular bandwidth of the log-Gabor filter respectively. 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:

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

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, from training images for the 1D Log-Gabor filters employed in this work.

IV. 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 three matchers considered in this work. The finger dorsal imaging setup is same as employed in [7]. The images were acquired in the outdoor and also in indoor environment from male/female volunteers in the age group of 4-60 years. The finger dorsal surface images from the first 10 subjects in this database were employed to select the best set of parameters for the 1D Log-Gabor filter and LBP. 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, similar to as in [6]-[7], as the knuckle images have high variations within the same class which can be attributed to shadows, illumination, scale, pose variations and the limiting 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). However due to limited availability of space in this paper, the major finger knuckle segmentation algorithm is not further described.

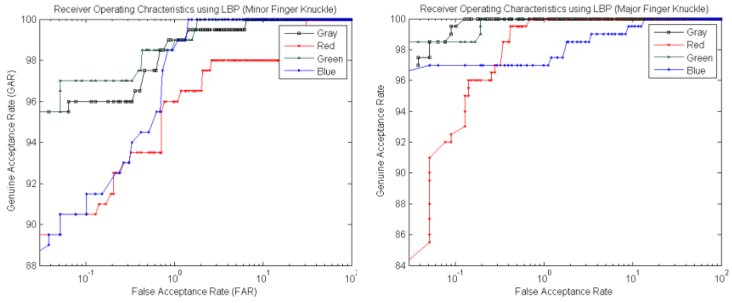
The *minor* finger knuckle segmentation algorithm developed in this paper achieves quite accurate segmentation. However the stability of the segmented region may vary for the finger dorsal images even from the same subject and this can be attributed to the absence of user-pegs or constraints for the finger movement between successive imaging. The limiting stability of segmented region is a reasonable tradeoff‡ for the enhanced user convenience and the accuracy of the 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 50 subject database are summarized in table 1 with their corresponding receiver operating characteristics (ROC) shown in figure 4-6. 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 achieve high accuracy, *i.e.*, equal error rate of 0.5%, 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 1D Log-Gabor filters can achieve superior than those using LBP or ILBP approach considered in this work.

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

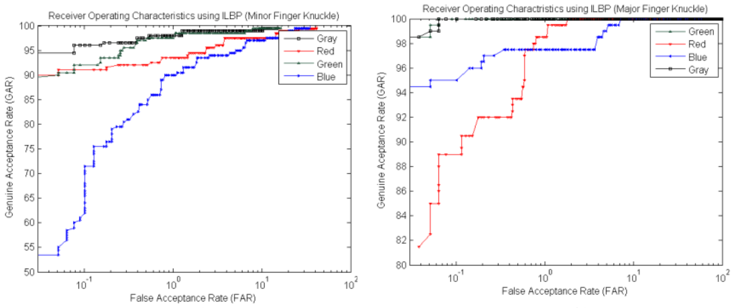
	Local Binary Pattern				*Improved Local Binary Pattern*				*1D Log-Gabor*
	Red	Green	Blue	Gray	Red	Green	Blue	Gray	Gray
Minor Knuckle	2.5%	1.01%	1.08%	1.0%	3.7%	1.5%	5.12%	1.25%	0.5%
Major Knuckle	0.5%	0.2%	1.75%	0.12%	1.27%	0.6%	2.5%	0.6%	0.09%

‡ 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).



(a) (b)

Figure 4: Receiver Operating Characteristics using LBP matcher using segmented (a) *minor* finger knuckle images and (b) major finger knuckle images.



(a) (b)

Figure 5: Receiver Operating Characteristics using ILBP matcher using segmented (a) *minor* finger knuckle images and (b) major finger knuckle images.

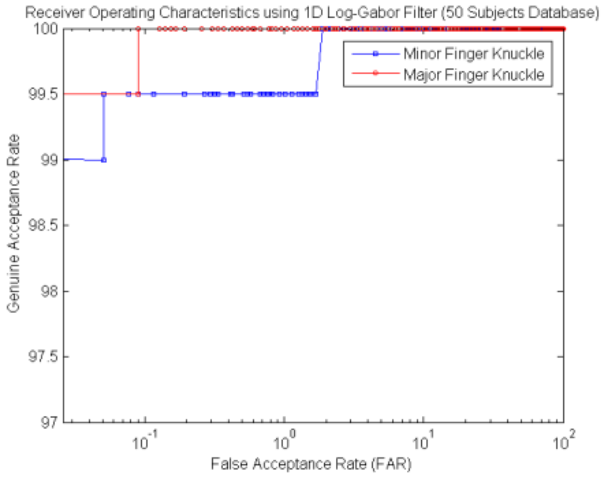


Figure 6: Receiver Operating Characteristics using 1D Log Gabor filter based matcher using segmented minor and major finger knuckle images.

The finger dorsal image database used in first set of experiments (table 1) was gradually enlarged and we have now developed a larger dataset [16] with 202 subjects with 5 images per subject from the middle finger images. The images from the first 10 subjects were used to compute best set of parameters while those from remaining 192 subjects were employed for the performance evaluation. The performance evaluation using this larger dataset generated 960 (192 × 5) genuine and impostor 183360 (192 × 191 × 5) matching scores. The distribution of genuine and impostor matching scores from the corresponding *minor* and major knuckle images are illustrated in figure 7. The ROC from this

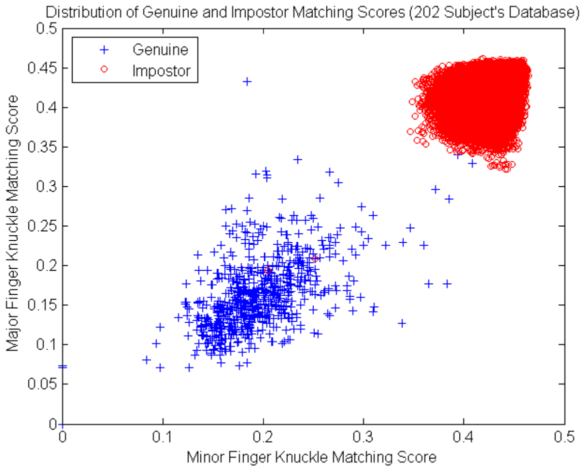


Figure 7: Distribution of genuine and impostor matching scores from the simultaneously extracted *minor* finger knuckle images and major finger knuckle images.

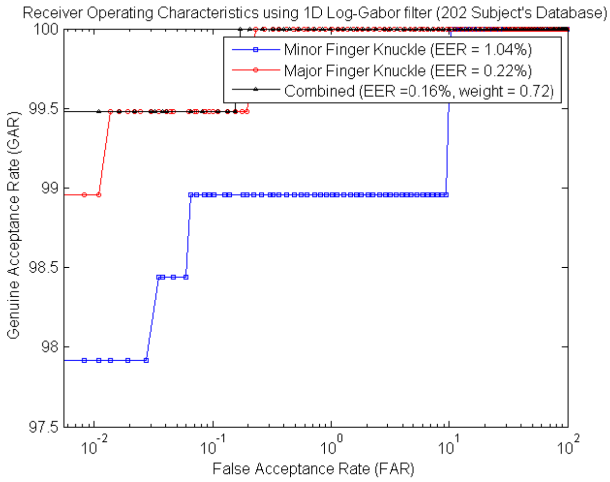
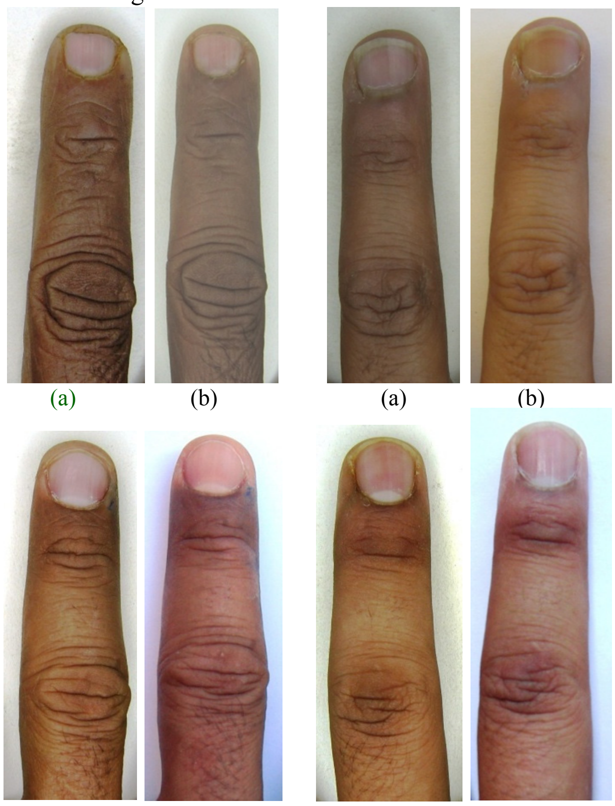


Figure 8: Receiver Operating Characteristics for 202 subject database using 1D Log-Gabor filter based matcher.

set of experiments is shown in figure 8. The equal error rate for the *minor* finger knuckle matching and major finger knuckle matching was respectively 1.04% and 0.22 %. In order to ascertain the performance improvement for the major finger knuckle matchings, by simultaneously utilizing *minor* finger knuckle images, the score level fusion was employed. The weighted combination of matching score has shown to generate best performance in many/most cases [18] and was therefore pursued in this work. The weights of 0.72 (major knuckle) and 0.28 (minor knuckle) were computed from the training dataset of first 10 subject and used in the experiments. The equal error rate from the combination further dropped to 0.16% and the corresponding ROC is illustrated in figure 8.

V. Conclusions

This paper has successfully investigated the possibility of employing *minor* finger knuckle images for the biometric identification. The coarse-to-fine segmentation strategy developed/detailed 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 202 subjects, achieve 1.04% EER from only using *minor* finger knuckle images. The achieved results 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.



(a) (b) (a) (b)

(a) (b) (a) (b)

Figure 9: Middle finger dorsal images with knuckle texture patterns from four different subjects. Images in (a) were acquired in 2006 in *indoor* environment while images in (b) were acquired in 2012 in *outdoor* environment. The variation in imaging distance and environment has have also changed the appearance of second time images.

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 6-10 weeks, to ascertain the stability their stability in respective duration. Lack of any large scale study on the individuality and stability of finger knuckle patterns has cautioned the use of finger knuckle images for any commercial applications. There is pressing need to ascertain performance from finger knuckle images on large scale databases (1000+ subjects) and also the stability of such pattern over several months/years to make some scientific conclusions on the stability of such patterns. In our ongoing study, we have now acquired database from subjects after the interval of more than **5 years** and some of these images are reproduced in figure 9-10. Careful visual inspection of these images (and others) in our database points towards high degree of stability in the curved lines and creases 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 using finger images.

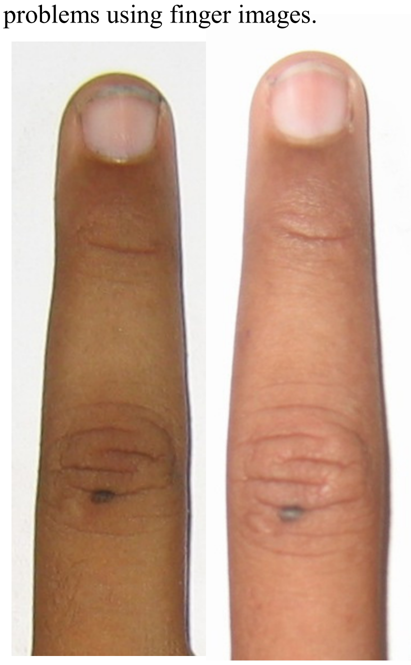


Figure 10: Middle finger dorsal image of a volunteer; (a) at the age of ~ 14 year and (b) at the age of ~17 years acquired after 3+ year's interval.

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 more 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. The experimental evaluation from *minor* finger knuckle images presented in this paper using cross-validation has shown exciting results but further work/evaluation is required to ascertain performance using minimum number of training images and to ascertain average recognition performance from such images. Although a lot more work remains to be done, the results presented in this paper indicate that the human identification using '*minor*' or '*upper*' finger knuckle images can constitute a promising addition to the biometrics security, especially for image forensics and surveillance applications using finger images.

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