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Personal Identification Using Knuckle

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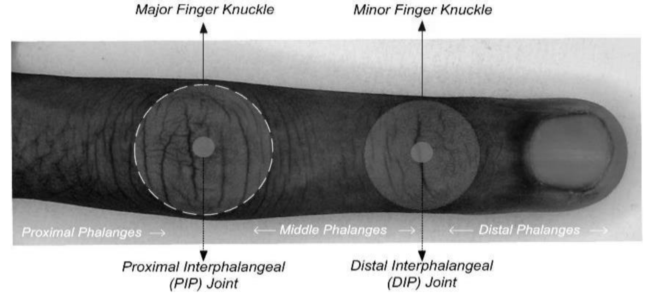
Abstract— The work detailed in this project also investigated the potential for visible illumination palm dorsal images as a biometric identifier. Automatically segmented images from 501 subjects, with significant majority of them acquired under outdoor illumination, were used to ascertain matching capability from such potential identifier and encouraging results were obtained. Our results also demonstrated that the combination of finger knuckle patterns and simultaneously extracted palm dorsal regions can be used to further improve knuckle matching performance. The results presented from these set of experiments should be considered preliminary, indicating great potential for this region to serve as biometric, and require further work to achieve more accurate performance

I. INTRODUCTION

Automated identification of humans using their unique anatomical characteristics has been increasingly investigated for their applications in human surveillance and image forensics. 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 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 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 the nature of information that can be extracted from the finger dorsal images. This focuses on this problem and investigates the possibility of using minor finger knuckle patterns for the biometric identification.

Finger Knuckle

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.



SURVEILENCE:

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.

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IMPACT SURVEILENCE:

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 project is motivated to check the veracity of the questions and assertions (we received during peer reviews on earlier projects [3], [7]) that the stability of finger knuckle patterns, especially for forensic and law-enforcement has never been explored/established.

VISUAL SURVEILLANCE:

The full potential of automatic surveillance systems for applications like content-based retrieval of surveillance video and detection and prediction of abnormalities will only be achieved if the system can be applied in an unconstrained environment.

CHANGES IN ILLUMINATION:

Many surveillance systems work in an outdoor environment monitoring e.g. parking lots, sports arenas, railway stations, or industry complexes. The outdoor environment will be affected by very large changes in illumination. The most important light source will be the sun, but also artificial lights may be present and cause different local illuminations. Illumination from the sun will change remarkably over the course of a day, and the influence of the artificial light sources will change accordingly.Cloudy weather will further add to the changes in illumination, and these changes will occur rapidly on windy days. Putting constraints on the illumination conditions handled by the surveillance system will effectively mean that reliable results could only be expected for short periods of time.

BACKGROUND DYNAMICS:

The outdoor environment also introduces the challenge of non-static backgrounds. Constraints regarding the dynamics of the background will limit the system to only monitor certain areas, where the dynamism is limited.

E. OBJECT MOTION:

In an open area the objects will be able to move in any direction, and with a camera setup typical of surveillance systems, this will give movement in all directions of the surveillance video, and objects will enter and leave the field of view on all its boundaries

People may also be moving in groups or form and leave groups in an arbitrary fashion. These challenges could be solved by restricting the movement of the objects, but this would limit the system from being applied in many situations.

BACKGROUND MODELING:

Firstly, video frames captured from a camera are input to the background subtractor.Preprocessing stages are used for filtration and to change the raw input video to a process able format. Background modeling then uses the observed video frame to calculate and update the background model that is representative of the scene without any objects of interest .The background model can deal with events such as objects changing positions by implementing an effective update rule to change the model over time

OBJECT TRACKING:

In order to allow high-resolution images of the people in the scene to be acquired it is reasonable to assume that such people move about in the scene. To monitor the Scene reliably it is essential that the processing time per frame be as low as possible. Hence it is important that the techniques which are employed are as simple and as efficient as possible.

FINGER KNUCKLE IMAGING AND REGION OF INTEREST SEGMENTATION

The key region of interest in this investigation represents region of image between metacarpal and the proximal phalanx from the finger dorsal surface. This region of interest is automatically segmented from the hand dorsal images employed for this work. The hand dorsal surface images from the right hands of volunteers were acquired using contactless hand imaging. The imaging setup is similar to as the one employed in reference. However in addition to the indoor illumination, the majority of images in the developed database were acquired under outdoor (ambient) illumination. 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 show n 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, similar to as detailed in reference, is performed and utilized in this work (not described here as more details can be referred from). Majority of images employed in this work were acquired under outdoor environment u sing hand held camera. The distance between the hand held digital camera and hand dorsal surface in contactless imaging is not fixed. Such variations in the distances often generate hand dorsal images with varying scale and therefore scale normalization of the acquired images is performed. This is achieved by normalizing the acquired images to a fixed scale. The scale factor for such normalization 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 all our experiments).

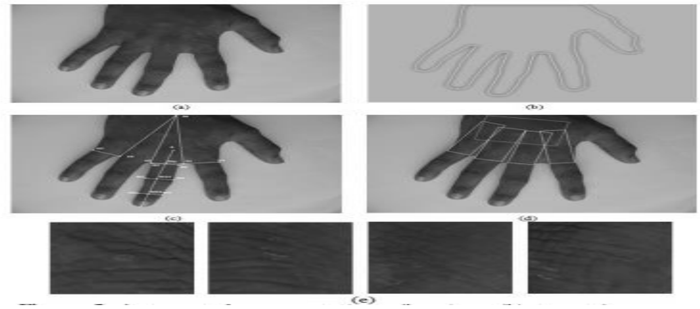


Figure 2: Automated segmentation of region of interest (second minor finger knuckle);

(a) acquired image sample under outdoor illumination, (b) recovered hand contour image (enhanced for easy visualization), and (c) localization of key points. The red squares in figure (d) illustrate the localized second minor finger knuckle region and the corresponding segmented knuckle images are shown in (e).

The key points corresponding to (four) finger tips and mid -point of two base points for each of the finger are used to further localize the second minor finger knuckle region of interest. The line joining finger-tip (top point) and the base point (mid -point of v1 and v2) is fu rther 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 from our database and their automatically localized second minor knuckle regions are also highlighted as the red color boxes.

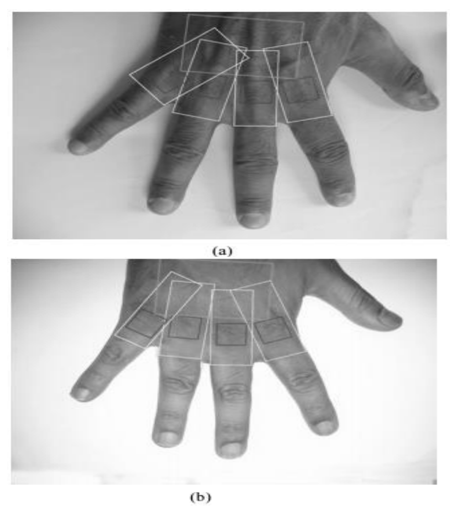


Figure 3: Image samples from two volunteers acquired under outdoor (a) and in indoor (b) environment. The red

boxes 100 illustrate automatically localized and segmented 100 pixels ROI to ascertain their possible usage as a biometric trait.

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 show n 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, similar to as detailed in is performed and utilized in this work . Majority of images employed in this work were acquired under outdoor environment u sing hand held camera. The distance between the hand held digital camera and hand dorsal surface in contactless imaging is not fixed. Such variations in the distances often generate hand dorsal images with varying scale and therefore scale normalization of the acquired images is performed. This is achieved by normalizing the acquired images to a fixed scale. The scale factor for such normalization 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 all our experiments). The key points corresponding to (four) finger tips and mid - point of two base points for each of the finger are used to further localize the second minor finger knuckle region of interest. The line joining finger-tip (top point) and the base point (mid -point of v1 and v2) is further extended by an amount one third of finger length 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 from our database and their automatically localized second minor knuckle regions are also highlighted as the red color boxes.

BLOCK DIAGRAM

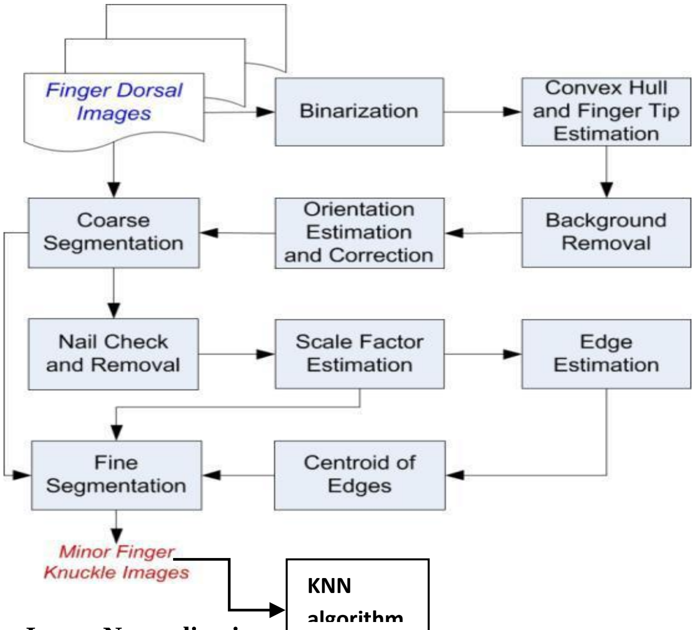


Image Normalization

The finger dorsal images are acquired from the curved 3D knuckle 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 image enhancement steps are essentially required to normalize such illumination variations in the ROI images. The illumination normalization approach used in this work is same as also used. This approach firstly estimates the average 16 pixels sub-blocks background illumination in the 16 of the segmented knuckle images. The estimated illumination is then subtracted from the original knuckle image to suppress the influence of uneven illuminations. The resulting image is then subjected to the histogram equalization operation which generates enhanced finger knuckle image for the next or feature extraction stage. Figures (b1)-(b5) and (c1)-(c5) illustrate second minor finger image samples before and after the image enhancement operations respectively. These images illustrate that employed enhancement approach has been quite effective for enhancing the knuckle creases and curves from the automatically segmented second minor knuckle images.

Feature extraction and matching

The second minor finger knuckle images after the image enhancement illustrate randomly textured patterns which appears to be quite unique in images from different fingers/ subjects. Such patterns typically consist of creases, lines, and wrinkles of varying thickness, which alsovaries with the forward movement of respective fingers. A new approach to match such second minor knuckle images is investigated and detailed in the next section. We also comparatively evaluated several matching strategies to be effective in matching palm or major finger knuckle patterns in the literature. These are also briefly described in following.

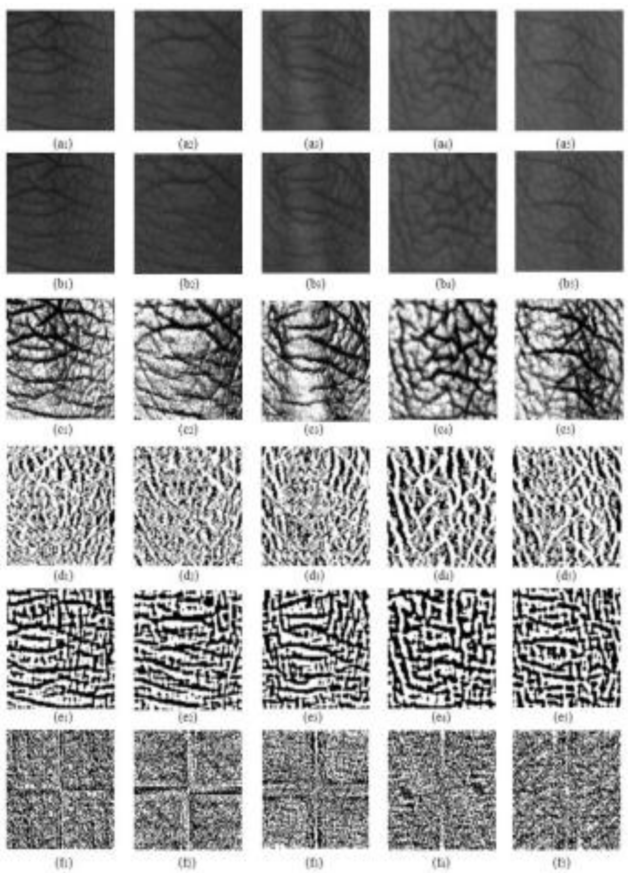


Figure 5: Automatically segmented lower or second minor knuckle images corresponding to middle finger images of five different subjects in (a 1 -a5) respectively. Corresponding grey-level images in (b1 -b5), enhanced images (c1 -c5), KnuckleCode or RLOC representation (d 1 -d5), Ordinal representation for 30 deg (e1 -e5), and spectral representation using BLPOC in (f1 -f 5).

Local Feature Descriptor

The second minor finger knuckle images typically illu strate texture-like details which are random but appears to be quite unique for each of the fingers. These texture patterns can be more effectively and efficiently matched from their spatial feature similarity in local regions. Therefore a new spatial-domain approach to match the knuckle patterns was investigated in this work. A spatial filter is employed to perform convolution with the knuckle images and the quantization of resulting filter response generates respective features corresponding to chosen quantization levels. The two-level quantization can provide compact or smallest size template representation and also generate fast similarity scores using computationally simpler Hamming distances. The features generated from such spatial filtering are expected to encode features which are localized and represents the neighborhood pixel information. The size of this spatial filter defines the scope of this neighborhood. The larger (smaller) filter size is expected to encode more global (local) information and vice versa. Let the shape of this spatial filter be a square to ensure symmetry, then the simplified filter (i, j) can be constructed as follows:

$$f(i,j) = \begin{cases} -(2N+1)^2+1 & if\ i=0\ \&\&\ j=0 \\ 1 & otherwise \end{cases} \qquad (1)$$

where i, j is index in the filter, $i, j \in [-N, N]$, and N defines the scope of neighborhood. The filtered response from a point on knuckle surface is essentially the sum of difference between the point and each of its neighboring points. If the local grey level continuity is to be ensured, like in knuckle or natural images, the difference between grey levels from two points which are close to each other should almost be zero. Therefore the sum of them should also be very small and the binary feature (x, y) for the point (x, y) in knuckle image I can be computed as follows:

$$K(x,y) = \begin{cases} 1 & if\ I(x,y) * f(i,j) > 0 \\ 0 & otherwise \end{cases} \qquad (2)$$

where $*$ represents pixel-w ise convolution operation. When the encoded feature from (2) is one, the local knuckle shape is expected to concave else the described shape is more likely to be convex. It is generally believed that the gradient of descriptors can offer more powerful capability to describe the feature. Therefore the gradient version of filter (i, j) in (1) is expected to generate more powerful feature descriptor. We partition the neighbors of a given point (x, y) into two subsets whose spatial extent or size is the same. For all the points or image pixels in the two subsets, we subtract their value from (x, y). After computing the sum of points' values for each subset, the gradient is defined as the difference between these two respective/ sum results. Let these two subsets be represented as $D1$ and $D2$, then the gradient filter $g(i, j)$ obtained from $f(i, j)$ can be defined as follows:

$$g(i,j) = \begin{cases} -1 & \text{if } point(i,j) \in D_1 \\ 1 & otherwise \end{cases} \quad (3)$$

There can be several possibilities to explore the spatial extent of partitions $D1$ and $D2$. In this work we only considered simplified partitions to define $(i,\ j)$ as follows:

$$g(i,j) = \begin{cases} 1 & \text{if } abs(i) < abs(j) \\ -1 & \text{if } abs(i) > abs(j) \\ 0 & \text{if } abs(i) = abs(j) \end{cases} \quad (4)$$

where $i,\ j$ is index in the filter with $i,\ j \in [-N,\ N]$ and $abs(\cdot)$ is the absolute operation. The matching distance sf between the two feature matrix, i.e., one obtained from the gallery (G) and the probe (E), is computed as follows:

$$s_f = \frac{1}{(n-q)(m-p)} \sum_{y=1}^{m-p} \sum_{x=1}^{n-q} XOR\big(G(x,y), E(x,y)\big)$$

where $XOR(G,\ E)$ is the Boolean XOR operator that computes Hamming distance between two binarized template G and E while m and n denotes the spatial size of these templates. In order to accommodate possible translations between the knuckle surface, we translate the binarized templates of the probe in horizontal q and vertical direction p and perform multiple matches. These translations are performed in two steps for four directions (left, right, up, down) in steps of two pixels. The best or smallest of Hamming distance among these translations is used as final similarity score sf (5) between the two matched templates.

Band Limited Phase Only Correlation

Another possible approach to match these knuckle patterns is to compute their similarity or correlation from their spectral representations. Such an approach has shown to offer more accurate results and was therefore attempted to match second minor knuckle images. This approach only uses phase information recovered from the 2D discrete Fourier transform (DFT) of the segmented knuckle images and therefore least sensitive to the translation/ rotational changes. In order to minimize the influence noise, only a band of frequency in the DFT representation is employed for the matching. This approach detailed in [17] is briefly summarized in the following. Let 2D DFT of two P × Q pixels normalized knuckle images, say S1 (x, y) and S2 (x, y), be respectively represented as F1 (k1 , k2) and F2 (k1 , k2).

Local Radon Transform

Matching knuckle images using Local Radon Transform (LRT), referred to as RLOC or Knuckle Code representation in, has to be quite effective in accurately matching the major knuckle patterns and was therefore also evaluated 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 are matched using the Hamming distance. The details of this approach can be found in reference. The key advantage of this approach is that it produces smaller template size and is computationally efficient in generating templates than BLPOC, and also the ordinal representation approach considered for the performance comparison. Another approach referred as (fast) CompCode , which is quite similar in encoding local knuckle crease orientations but using even Gabor filters, was also evaluated for the comparative performance.

Ordinal Representation

The ordinal measures typically compute measurements that are based on the relative distances . The ordinal representation of textured like surface such as palm and iris has show n to offer promising results and therefore this method was also evaluated to ascertain its accuracy in matching the knuckle images. Similar to as detailed in reference , 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 matches.

.EXPRIMENTS AND RESULTS

The experiments were performed in several phases to ascertain the usefulness of second minor finger knuckle patterns for the biometric authentication. We acquired hand dorsal images from 501 different subjects using contactless hand imaging. The images were acquired from the right hand of the volunteers under 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 2. These images were enhanced and subjected to the feature extraction using three matchers as discussed in section 3. 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 . Two Gaussian filters (size was 11 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.

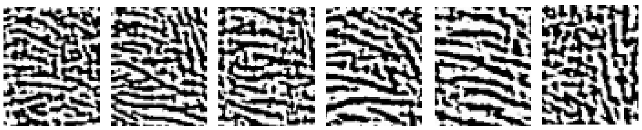
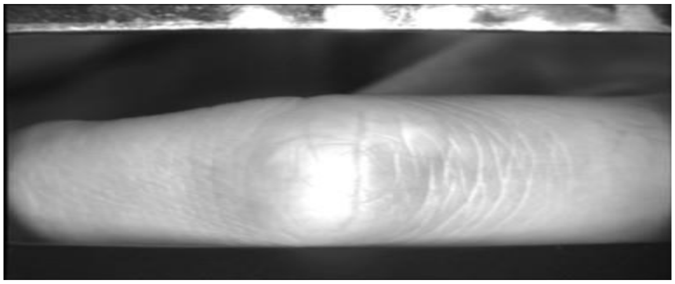
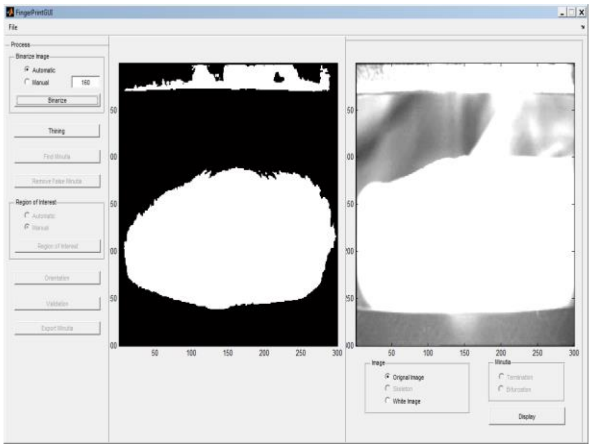


Figure 6: Typical samples of templates generated from six different subjects' second minor knuckle using local features

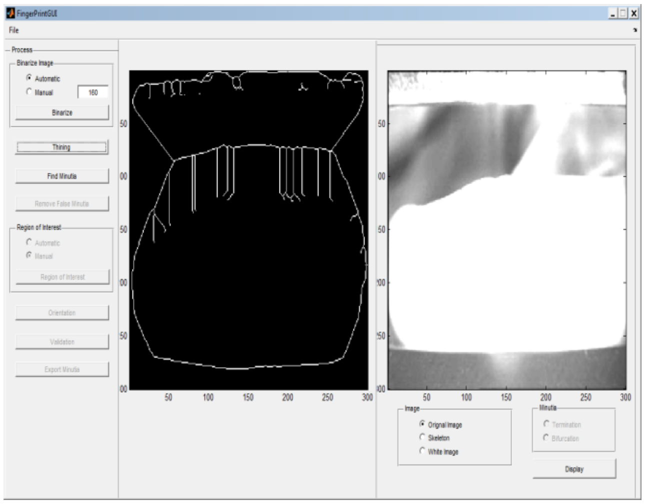
The first sets of experiments were performed to ascertain the suitability of matcher and its performance for the second minor finger knuckle patterns. We utilized five images from each of the four fingers, for every subject, and employed relatively challenging protocol (all-to-all instead of leave one-out) for matching second minor knuckle images. Therefore 5010 (501 × 10) genuine scores and 1252500 5×500) impostor scores were computed. The matching(501 performance was evaluated using the receiver operating characteristic (ROC).. It can be ascertained from these ROCs that the local feature based matcher evaluated in this work performs the best among five matchers considered for the performance comparison. The equal error rate (EER) from different matchers is also presented in table 1. In terms of EER, the performance of this approach can be considered to be similar to the BLPOC although BLPOC marginally performs better in some cases. It should however be noted that ROC rather than EER is widely considered as the reliable criterion for performance comparison. The complexity of BLPOC that requires computation of 2DFFT is also significantly high. Therefore we employed only the outperforming matcher (figure 7) using local features for other further experiments reported in this project.



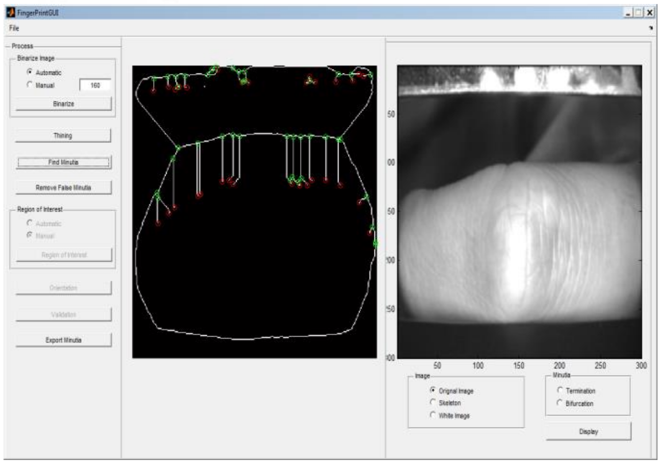
ORIGINAL OUTPUT



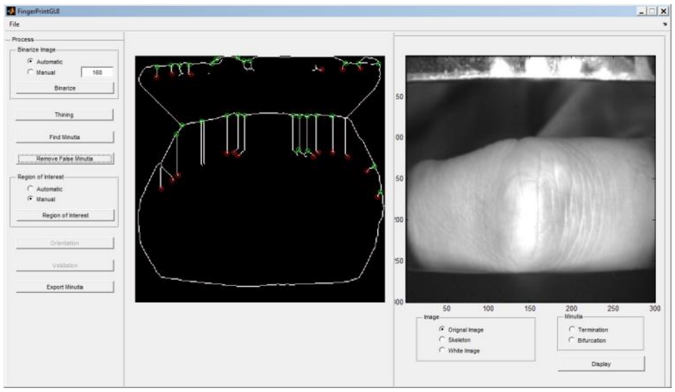
(B) **BINARIZE**



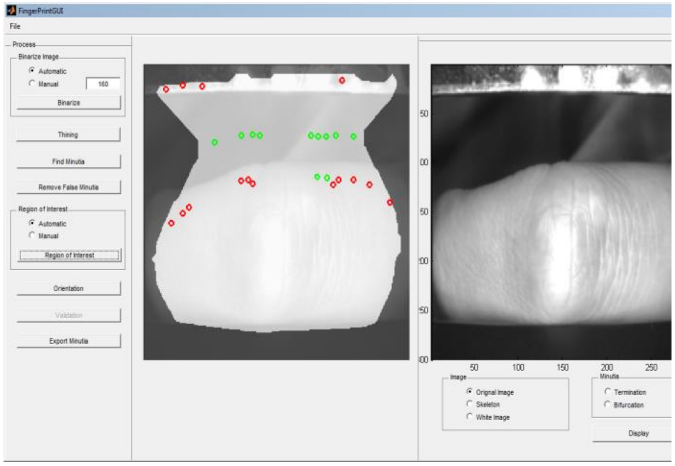
THINNING



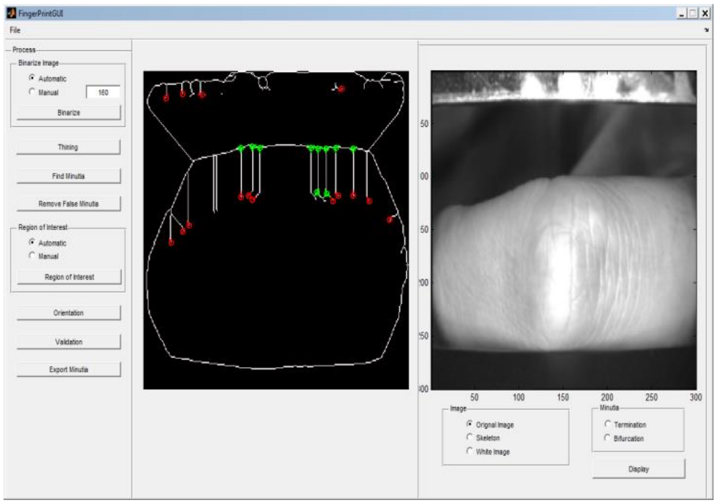
FIND MINUTIA



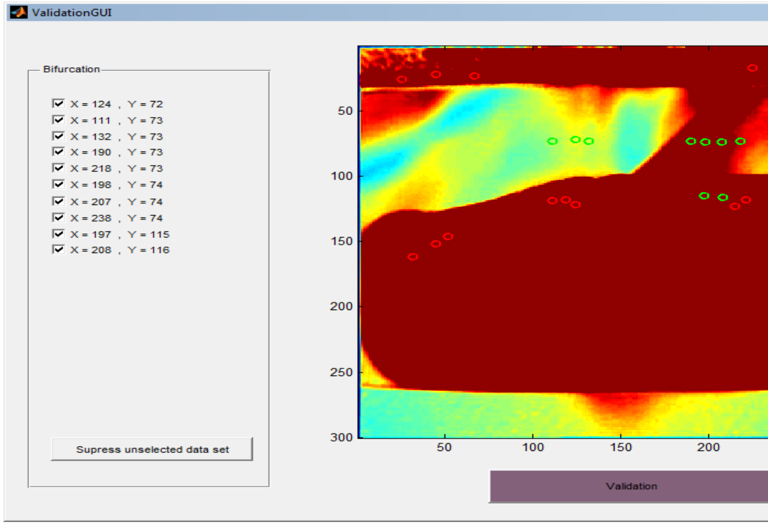
(D) **REMOVE FALSE MINUTIA**



(E) REGION OF INTEREST



(F) **ORIENTATION**



(G) **VALIDATION**

Figure 7: Typical samples of templates generated from three different subjects' second minar knuckle using local features

This project has investigated the possibility of using second minor finger knuckle image for the personal identification. The approach described in this project is completely automated and uses contactless imaging which is expected to produce/ accommodate large variations in images. The experimental results on the image database from over 500 subjects presented in this project suggest great potential for the second minor knuckle patterns to be employed as a biometric identifier. We also investigated a computationally simpler method of matching such knuckle patterns using local features and achieved out performing results. The experimental results presented in this project also suggest that the combination of simultaneously acquired/ available major, first minor and second minor knuckle patterns can achieve superior performance which is not possible from any of the three finger knuckle patterns alone. The work detailed in this project also investigated the potential for visible illumination palm dorsal images as a biometric identifier. Automatically segmented images from 501 subjects, with significant majority of them acquired under outdoor illumination, were used to ascertain matching capability from such potential identifier and encouraging results were obtained. Our results also demonstrated that the combination of finger knuckle patterns and simultaneously extracted palm dorsal regions can be used to further improve knuckle matching performance. The results presented from these set of experiments should be considered preliminary, indicating great potential for this region to serve as biometric, and require further work to achieve more accurate performance.

CONCLUTION

We introduce KNN algorithm (K-Nearest Neighbor)that is used to increase the accuracy of the image to 91% .Therefore it is important to investigate the uniqueness and stability in the piece of information from finger dorsal image.This project has investigated the possibility of using second minor finger knuckle image for the personal identification.The approach described in this project is completely automated and uses contactless imaging which is expected to produce/ accommodate large variations in images.The experimental results on the image database from over 500 subjects presented in this project suggest great potential for the second minor knuckle patterns to be employed as a biometric identifier**.**

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