# **Contactless Finger Knuckle Identification using Smartphones**

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Abstract—This paper details the development of a smartphone based online system to automatically identify a person by using their finger knuckle image. The key objective is to exploit user-friendly biometric, with least privacy concern, to enhance security of the data in smartphone. The final product from this research is a finger knuckle authentication smartphone application, which is developed under Android operating system with environment version 2.3.3. This paper has developed some specialized algorithms for the finger knuckle detection, image pre-processing and region segmentation. Automatically detected and segmented finger knuckle images are used to encode finger knuckle pattern phase information using a pair of log-Gabor filters. Efficient implementation of various modules is achieved in C/C++ programming language, with OpenCV library, for online application. We also developed a user-friendly graphical user interface for the users to enroll and authenticate themselves. The developed system can therefore acquire finger knuckle image from the smartphone camera and automatically authenticate the genuine users. This paper has also developed a new smartphone based finger knuckle image database of 561 finger knuckle images of 187 different fingers from 109 users, in real imaging environment. In the best of our knowledge, this is the first attempt to develop a mobile phone based finger knuckle identification which has shown highly promising results in automatically identifying the users from their finger knuckle images.

#### I. INTRODUCTION

A UTOMATED personal identification systems have emerged as an essential component of information systems with the wide range of applications from e-business to the law enforcement security. The advantages of automated personal identification are huge as they enhance reliability and security in e-business transactions which often outweigh the privacy related concerns in the usage or the deployment of such technologies.

In order to identify a person, the most popular method is to use the assigned username and a secret password. While passwords are mostly based on plain text, it is cumbersome to remember them. In addition, we often have multiple passwords to remember for different accounts and applications; some of them may only use numeric symbols as password (e.g. ATM); some of them may start with alphabet and also combined with numeric which not less than eight digits (e.g. most E-mail). Moreover, with increasing security requirements, it is not only required to have numeric and alphabet combinations, but some additional symbols are also required in password patterns. In summary, increasing demand for higher security from multiple applications, it is not uncommon for people to have more than 3 or 4 password patterns (some may have different password patterns for different login systems). Therefore the biometrics authentication can be promising alternative for more convenient personal identification. The usage of biometrics can help to alleviate the requirement of remembering long and cumbersome passwords, especially for mobile phone *applications* in which the *users are tied more frequently* than any other system.

There have been several promising efforts in the literature to exploit finger knuckle image pattern images for the automated personal identification. Reference [1] details an automated system which acquires hand dorsal images in contactless manner. Authors have exploited key finger points to reliably segment finger knuckle images in absence of any pegs while simultaneously utilizing the finger geometry features to boost the identification accuracy. There are several other interesting efforts in the literature which have exploited hand docking frame [13] or finger docking frame [3] to ensure minimum variations in the images acquired during the successive imaging. Reference [12] details another promising approach to recognize finger knuckle image patterns using KnuckleCodes. The KnuckleCode is essentially a Radon transform based representation of finger knuckle creases and curves to a two dimensional space. A multi-modal approach for the personal identification using finger geometry, knuckle images and palm print features appears in [2] while [23] investigates possibility of using *minor* finger knuckle images as biometric. Earlier studies acquired images using arrangements that require the user to partially touch [1] some surface or hold some frame [3]. Therefore those arrangements in reference [1], [3] [15] are not completely contactless. None of these studies have attempted to exploit smartphones for imaging or for the online identification.

#### A. Our Work

The main objective of this paper is to use commonly available smartphone to identify a person by using their finger knuckle images acquired from the available embedded camera. The idea is to exploit finger knuckle image pattern, instead of fingerprint pattern, which have least privacy concerns. It may also be noted that recent large scale proof of concept study conducted by UIDAI has recently estimated [18] that ~1.9% of subjects cannot be reliably authenticated using their fingerprints while similar study performed by NIST has also estimated [19] that ~2% of the subjects do not have sufficient quality fingerprints to be capable of use in commercial systems. The fingerprint biometric has been historically associated with criminal investigations and therefore some people often have stigma of criminal investigation with the fingerprint biometrics. The use of finger knuckle images can provide a promising alternative for such finger based biometric identification.

An automated online smartphone application that can allow the user/owner to access the system when embedded camera is presented with a finger dorsal image and verify the true identity is expected to have wide range of application in consumer and civilian applications.

This paper has attempted to develop such an online system to identify the finger knuckle image on the smartphones. The developed system/application can operate on any smartphones which uses Android operating system and contains an embedded camera (with at least 2 Mpixel resolution). This developed detection, segmentation, image normalization and matching algorithms have been implemented to achieve efficient and accurate finger knuckle identification. The implementation of multiple finger knuckle image enrollments offers additional convenience to use any of the enrolled fingers for the identification. This paper uses 1D log-Gabor filter [16] to extract the finger knuckle templates which are matched using Hamming distance. We have also developed [17] a mobile phone based finger knuckle image database from 109 subjects with 187 different fingers to further research efforts in this area.

# II. FINGER IMAGE ACQUISITION AND KNUCKLE DETECTION

An online application should not only be able to automatically detect the region interest (knuckle) but also able to robustly segment and normalize the image for the feature encoding. The approach developed and implemented in this paper is summarized in the following sections.

#### A. Automated Finger Knuckle Detection

Automated detection of finger knuckle regions can be efficiently be performed by using AdaBoost based cascaded classifiers as constructed for face detection modules. The AdaBoost algorithm can automatically construct a strong classifier, using a linear combination of weak classifiers, from the training data consisting of positive (knuckle) and negative (non-knuckle) images. Such modified AdaBoost algorithm has been implemented in OpenCV [5] library and used (CreateSamples and HaarTraining modules) in this work. We have used 1,567 positive samples during the training. Among these 790 positive samples available from IITD Finger Knuckle [6] database were employed while the remaining positive samples were acquired from the smartphone HTC Desire HD A9191. All of the training samples are in grayscale and were resampled to size of 80  $\times$ 100 (width  $\times$  height) pixels.

The training stage for building cascaded classifier used 1,567 positive samples and 4,000 negative samples. Among 4000 negative samples, 3,000 of them were acquired from the web and the remaining negative samples were acquired from the HTC Desire HD A9191 smartphone. The variation in training parameters can influence the training results and we employed a total of five set of cascaded classifiers corresponding to different input parameters. All of these are training in 20 different stages. The performance evaluation of the training cascaded classifier used 100 independent test samples which had finger knuckles with varying size/pose. Table 1 summarizes the performance results. It contains 3 columns to illustrate the test results, i.e., Hits, Missed and False, which have conventional meaning. Table 1 shows the summary of the testing performance for each cascade classifier results.

Table 1: Summar	y of finger	knuckle det	tection	performance
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Cascade Classifier File	Hits	Missed	False	Accuracy*		
File 1	72	28	20	72%		
File 2	64	36	25	64%		
File 3	65	35	29	65%		
File 4	70	30	21	70%		
File 5	23	77	26	23%		
Accuracy = (Hits / number of testing samples) * 100%						

The most accurate results achieve 72% *hit rate* and are from File 1. If we include the numbers of false detection, there is 92% chances to detect an image which is a knuckle image. Therefore, for 100 test images, there are only 8 images that cannot be detected as knuckle images; 72 images are correctly detected and 20 images are with incorrect detection.

## B. Region of Interest Localization

It is necessary to provide an alternative and user friendly option to help users localize their finger knuckle images. This semi-automated choice is especially useful when image acquired has high background and/or illumination variations for which the trained classifiers may not precisely detect the knuckle regions. Therefore the option of center point localization, that can exploit built-in auto/macro focus module from the camera, is provided in the developed system. By using the smartphone, HTC Desire HD A9191 (which comes without Macro focus function in the embedded camera), with several experiments to acquire finger knuckle images at difference distances, the size of finger knuckle image for clearer and sharp image quality, is nearly 1/4 size of the entire image size when acquired from convenient distances. In order to acquire the best and larger finger knuckle image from embedded camera, the specific position and image size can be predefined. For example, an embedded camera with 3 Mega-Pixel ( $1536 \times 2048$ ) pixels, <sup>1</sup>/<sub>4</sub> of the size  $(768 \times 1024)$  pixels are used for finger knuckle image detection module. Figure 16 shows the finger knuckle image acquired from the embedded camera in real environment from our smartphone HTC Desire HD A9191. Figure 1(b) illustrated the center point in region of interest for a sample finger knuckle image and correspondingly localized knuckle detection area in figure 1 (a).



**Figure 1:** (a) Image acquired using smartphone, (b) the region of interest localized for the knuckle image detection.

## III. IMAGE PREPROCESSING

After the finger knuckle region has been detected and localized by using the algorithm discussed in Section II, the region of interest should be robustly segmented for the template generation. Figure 2 summarizes the key steps for such image pre-processing for the fine knuckle segmentation.



Figure 2: Image pre-processing steps.

# A. Fine Finger Knuckle Localization

Each of the coarsely localized finger knuckle image is subjected to fine location steps to extract the exact region of interest for the feature extraction. The coarsely localizes images from previous module are firstly subjected to the histogram equalization to minimize the influence of varying illumination and to adjust the contrast. This is followed by median filtering to suppress the speckle-like noise.



**Figure 3:** (a) Coarsely localized finger knuckle image, (b) region of interest image for the knuckle segmentation, (c) knuckle crease localization using Canny edge detector, (d) localized region with dominant edge density, and (e) finely segmented knuckle image.

The Canny edge detector on the coarsely localized knuckle image generates the boundaries of finger regions and also helps to localize the knuckle region. The edge detected image is used to estimate the edge density in every  $40 \times 50$  (width  $\times$ height) pixels region of this image. The center point of this region is used to extract the fixed size knuckle region (figure 3-e) for the feature extraction.

## B. Finger Knuckle Rotation & Segmentation

In order to accommodation rotational variations in the finger knuckle images, we can store multiple templates generated from the rotation of the acquired images and use the best matching scores to authenticate the user. In order to limit the computations we however only rotate portion of the acquired image. We rotate the images in the step of one degree and the images rotated +/- 5 degrees (this limit is determined using experiments and is a compromise between the performance and computational complexity). Therefore, there can be a maximum of 11 finger knuckles images from one finger which can help to generate best matching scores.

We attempt to normalize the images in such a manner that images of fixed size and aspect ratio are finally employed for the feature extraction. The ratio of the knuckle region width: height is empirically fixed as 4: 5 while the size of segmented images is normalizes (scaled to)  $160 \times 200$  pixels. We use bicubic interpolation to automatically scale the segmented images over a  $4 \times 4$  pixels neighborhood for the geometric transformations.



Figure 4: Spatial domain representation of real and imaginary components of 1D Log Gabor filters.

## IV. FEATURE EXTRACTION

The Gabor filters have shown to offer joint characterization of textural features in spatial and spatial-frequency domain. Log-Gabor filters [7] are highly suitable when the feature details are to be acquired from high-frequency areas (such as those from discriminative finger knuckle creases and edges) as these filters have null dc component and desirable high-pass characteristics. Log-Gabor filters can be constructed with arbitrary bandwidth, which it can be optimized in order to produce a filter with minimal spatial extent. The frequency response of Log-Gabor can be expressed as:

$$= e^{-\frac{\left[\log f_{O}\right]^{2}}{2\left[\log \frac{\sigma}{f_{O}}\right]^{2}}}$$
(1)

where  $f_0$  is the center frequency, and  $\sigma$  is the radial bandwidth of the Log Gabor filter. The spatial domain representation of 1D Log-Gabor filters is shown in figure 4.

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Each of the segmented and enhanced finger knuckle image is subjected to 1D Log Gabor filtering. The spatial domain response from the real and imaginary components of 1D Log Gabor filter is computed. This complex response is denoted as  $\psi$  and each pixel is encoded as '0' or '1' based on the filter response to obtain the template  $\varphi$ . The following inequalities can formulate the encoding of finger knuckle images in filtered image  $\psi$  for every pixel:

$$\varphi(i,j) = \begin{cases} 0, & \psi(i,j) < 0\\ 1, & \psi(i,j) \ge 0 \end{cases}$$
(2)

## V. TEMPLATE MATCHING

The binarized templates  $\varphi$  generated from every finger knuckle image is subjected to template matching to ascertain the similarity between claimed user identity and the input template(s) stored in the enrollment database. The degree of the similarity or the dissimilarity between two templates is determined using the Hamming distance. The normalized Hamming distance  $D_{PQ}$  between two  $M \times N$  size *complex* bitwise finger knuckle template, P and Q, is computed as follows:

$$D_{PQ} = \sum_{m=1}^{M} \sum_{n=1}^{N} \{P_r(m,n) \oplus Q_r(m,n) + P_i(m,n) \oplus O_i(m,n)\}$$
(3)

where  $\oplus$  is the XOR operator and  $P_r(P_i)$  denotes the real (imaginary) component of template P. Despite best of the efforts to robustly localize and segment the knuckle region images, some translational and rotational variations inherently remain even from the same user in successive imaging (primarily due to the *contactless* nature of imaging). Therefore we employ bit-wise shifting of knuckle templates, both in horizontal and vertical directions, and use the best/minimum matching distance to authenticate the user. Figure 5 (a) and (b) shows the Genuine and Imposter score distribution respectively.



**Figure 5**: Distribution of (a) genuine scores and (b) impost scores from 109 subject's images in our database.

## VI. SYSTEM DEVELOPMENT

## A. Programming Languages

The feature extraction and encoding operations using Log-Gabor filtering requires complex matrix operations which should be executed on real time basis. The effective CPU execution time is of high concern for the template matching using bit-by-bit comparisons (equation 3). The programming language benchmarks presented in reference [8] has rated C/C++ with the highest/preferred score among most popular languages employed for different operating system. Therefore, C/C++ programming language was also preferred for developing the purposed solution.

#### **B.** Development Environment

The smartphone we employed to develop and evaluate the finger knuckle authentication system is HTC Desire HD A9191 [9]. The details of the hardware specification of the phone are summarized in the following:

- Platform: Android <sup>TM</sup> 2.3.3 (Gingerbread)
- Camera: 8 Mega-Pixels Color Camera with Auto Focus
- CPU: Qualcomm Snapdragon S2 1GHz
- RAM: 768 MB
- Internal Storage (ROM): 1.5 GB

The Android [10] platform can not only support Java programming language to implement the application but it also supports the Android NDK [11] that allow developers to build up the performance critical portions of application in native code. With the NDK, it provides the headers and libraries that allow developers to program in C/C++ and fully control the application environment. Therefore, the Android Software Development Kit (SDK), in addition to Android NDK, was exploited for developing this application.

Figure 6 illustrates the developed user-friendly interface that interacts with users and uses the enrollment database to authenticate users. Figure 7 further illustrates the key steps for the user enrollment while figure 8 illustrates the user verification using the developed system.



Figure 6: User authentication developed interface.



Figure 7: (a) User presenting his index finger for registration, (b) firing of automated detection and segmentation module, (c) segmented and normalized knuckle region, (d) after selecting the "Enrollment" button, and (e) successful completion of enrollment process.



**Figure 8:** A verification process consisting of (a) knuckle image detection, (b) resulting normalized knuckle image, (c) template generation, and (c) verification. Successful verification is prompted (e) while failed verification for impostor knuckle image.

## C. Performance in Smartphones

We constructed an enrollment database from a user using his three templates generated during the enrollment stage and compared the verification time between  $C/C^{++}$  and Java implementations using the feature encoding and template matching scheme detailed in section III. Table 2 illustrates the verification time for this user, in 10 successive verification attempts.



Our test smartphone hardware platform is built with 1GHz CPU and 768 MB RAM. The execution speed of the system is superior when a faster CPU and a larger RAM is supported in the smartphone hardware. Since most of the popular Android smartphone in the market already had more than 1GHz CPU and more than 768 MB RAM, the real execution time would be better than those from our experiments. Therefore, the minimum supporting hardware requirement for an acceptable execution time, for the developed smartphone based knuckle authentication system, would be at least 1GHz CPU and 768 MB RAM.

# VII. EXPERIMENTS AND RESULTS

This work has also developed a smartphone based finger knuckle images database which is being made publicly/freely available [17] to promote further research/development efforts in this area. This database includes 561 images from 109 subjects. We also used 790 additional finger knuckle images (not in 561 image database) for the training stage during the development of AdaBoost based automated finger knuckle detector (section II-A) using Haar features.

The experimental evaluation was performed using the log-Gabor based finger knuckle template matching (equation 3) employed in this work. All the images in this database, from 187 different fingers, were used to generate genuine and imposter score distribution which has been illustrated in figure 5. The parameters of log-Gabor filter were determined during the training phase and were fixed during all the experiments, *i.e.*, the ratio  $\sigma_f / f_0$  (sigmaOnf) was fixed to 0.6, each of the templates were shifted by 8 bits and the best score among these matches (using equation 3) was used for the decision making. The corresponding receiver operating characteristics (ROC) is shown in figure 9. The equal error rate (~9%) is not quite low as can be possible from touch based conventional fingerprint authentication systems. However the achieved performance is encouraging as the images are acquired using contactless imaging, and more importantly the mobile phone is very likely to be accessed or used by few (~5-6) users, instead of 109 subjects finger knuckle employed for the performance evaluation, which can generate very small error rates suitable for practical applications.



Figure 9: The receiver operating characteristics for smartphone based finger knuckle identification for 109 subjects.

## VIII. CONCLUSIONS

In this paper, we have developed a contactless finger knuckle based personal authentication system that can operate by using smartphones. This is the first successful attempt to develop a finger knuckle based authentication system using smartphones in the best of our knowledge.

The developed system exploits the smartphone embedded camera (with auto focus capability) to acquire better quality images, perform multiple image processing operation to automatically detect and segment region of interest, extract finger knuckle features, matching them with the stored templates and presents the result of authentication to the (unknown) user. The developed application has shown to work satisfactorily. The developed application is an attractive alternative for the users (i) whose may not have fingerprints of sufficient quality for identification or (ii) who may have high concerns on the use of fingerprints and still want to ensure high security on their smartphones in most convenient manner. This paper has also developed [17] new finger knuckle database of 561 images acquired from 187 different fingers from 109 subjects that can be used by researchers and developers of this new biometrics technology. It is creative, unique and well designed for daily use application. While, there still some challenges encountered during the development period. But, the prototype is worked and is developed to demonstrate our system.

The main objective in this work was to exploit finger knuckle images for developing an automated authentication system for smartphones. In order to achieve such objective, we performed several tasks. Firstly, the automated capability for detecting the finger knuckle image region was introduced. This module extensively utilizes the automatically extracted Haar features from the acquired images and uses OpenCV library. The developed algorithm was implemented on Android operating system which is the most popular platform among the smartphones used today. There have been some promising efforts [21]-[22] to explore iris recognition using mobile phones. The iris recognition using mobile phone requires some modifications [22] to ensure availability of near infrared illumination for the imaging while the visible illumination iris recognition requires relatively significant cooperation [20] and in often perceived to be inconvenient with the single camera mobile phones. Therefore finger knuckle based personal identification can invite higher user acceptability, primarily due to ease in finger imaging and minimum privacy concerns/impact.

It may be noted that the execution time for the verification would increase sharply if the user stores many templates in the enrollment database. In our system, the maximum number of enrolled finger knuckle images for each user is set to 5. This restriction ensures that the average time for the user authentication does not exceed 5 seconds when the system is used only for the user authentication.

In order to ensure accurate finger knuckle detection, the acquire image background should be largely uniform as the background noise would influence the auto finger knuckle detect capability. In the current development, we have tried to enhance the algorithm to achieve improved detection of the finger knuckle images from the varying background in real imaging environments. However further efforts are required to ensure accurate detection and localization of finger knuckle, from the finger dorsal images with noisy background, as the limited segmentation accuracy significantly influences the identification accuracy.

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