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Improved Fingerphoto Verification System Using Multi-scale Second Order Local Structures

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Abstract: Today's high-end smartphones are embedded with advanced fingerprint biometric recognition systems that require dedicated sensors to capture the fingerprint data. The inclusion of such sensors helps in achieving better biometric performance and hence can enable various applications that demand reliable identity verification. However, fingerphoto recognition systems have some inherent advantages over fingerprint recognition such as no latent fingerprints, and it enables the possibility to capture multiple samples at once from a biometric instance with minimal user interaction. Thus, user authentication based on fingerphotos could be a useful alternative as we can re-use the smartphone camera to capture the fingerphotos. On the other hand, such an approach introduces different challenges; for example illumination, orientation, background variation, and focus resulting in lower biometric performance. In this research, we propose a novel verification framework based on the feature extracted from the eigenvalues of convolved images using multi-scale second order Gaussian derivatives. The proposed framework is used to authenticate individuals based on images/videos of their fingers captured using the built-in smartphone cameras. When combining with the commercial off the shelf (COTS) system, the proposed feature extraction technique has achieved the improved verification performance with an equal error rate of 2.76%.

Keywords: Fingerphoto verification, Smartphone biometrics, Contactless fingerprints, User verification, Vesselness Filter, Image Enhancement.

1 Introduction

In recent years, there has been tremendous growth in the application of biometric recognition as a vital factor in contemporary authentication mechanisms. From just unlocking a device to accessing bank accounts online, smartphone biometrics is used widely in billions of smartphones. Therefore, to have higher accuracy, the dedicated biometric sensors are embedded in today's smartphones. However, fingerphoto recognition systems have some inherent advantages over fingerprint recognition such as it leaves no latent fingerprints on the biometric sensor and it enables the possibility to capture multiple samples at once from a biometric instance with minimal user interaction. Furthermore, in comparison to the traditional methods where samples are captured in a constrained manner, fingerphoto based systems provide recognition in an unconstrained environment [Ma17]. Also by reusing the primary sensors such as built-in cameras, we could easily develop the fingerphoto recognition system.

In contrast to fingerprint recognition systems in smartphones, there are traditional systems based on optical scanning sensors which capture the input samples as an image of the

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presented finger [La13]. Similar to the contact-less optical fingerprint scanners, we can capture images of a finger with the smartphone camera, potentially removing the need for specialized hardware. However, this approach introduces other challenges such as illumination, focus, and orientation. Hence, it is necessary for a biometric system to be robust against these type of challenges. This work proposes a novel method to extract robust features from fingerphotos to improve the biometric verification performance.

Our approach is based on the likelihood of a pixel belonging to the fingerprint patterns, i.e., ridges and valleys. Considering the similarities between thin vessel-like structures and fingerprint patterns, we propose a novel verification framework. Our method is based on the enhanced images constructed by the calculation of the vesselness from eigenvalues of the Hessian matrix also known as the vesselness filter or *Frangi filter*. The vesselness filter is mainly based on the multiscale second order local structure of an image (Hessian Matrix) and is proposed by Frangi et al., in [Fr98]. Initially, the work is intended to enhance the vessel-like structures from X-ray angiographic images. This paper aims to extend the capabilities of *Frangi filter* to be used as a fingerprint feature detector by empirically modifying the sensitivity controlling constants of *Frangi filter*.

2 Related work

Biometric recognition based on fingerphotos has been investigated previously. However, most of these methods show lower biometric performance [RBY, MSR09, HTY10, DYB12, SNB12, TG15, Sa15]. In literature, many works have been proposed based on the minutia extraction, where authors have introduced different algorithms to extract minutia from input fingerphotos acquired using the smartphone camera [MSR09, DYB12, SNB12]. In [TG15] authors proposed a contact-less fingerphoto recognition system based on extracted SURF features from fingerphotos where the number of matched SURF features were used to obtain the similarity between the two input fingerphotos. Hiew et al. in [HTY10] proposed a biometric verification based on support vector machine (SVM), where SVM is trained on the multispace random projections (MRPs) of features extracted using Gabor filters.

Various efforts to establish a correlation between fingerprints and their corresponding fingerphotos have been made in recent years by many researchers. In [LK18] authors present the interoperability between legacy fingerprint databases and fingerphotos. [KK15] presents the low-cost contactless 3D fingerprint identification system based on the reconstruction of 3D features from 2D fingerphotos captured using a single camera. All of the approaches as mentioned above, heavily rely on the several pre-processing steps such as segmentation of the region of interest, and its enhancement [RBY, MSR09, HTY10, DYB12, SNB12, TG15, Sa15].

The rest of the paper is divided into Section 3 which presents the proposed method. Section 4 describes the database used in this paper. Followed by the section providing the details of experiments and obtained results. Finally, Section 6 gives the concluding remarks.

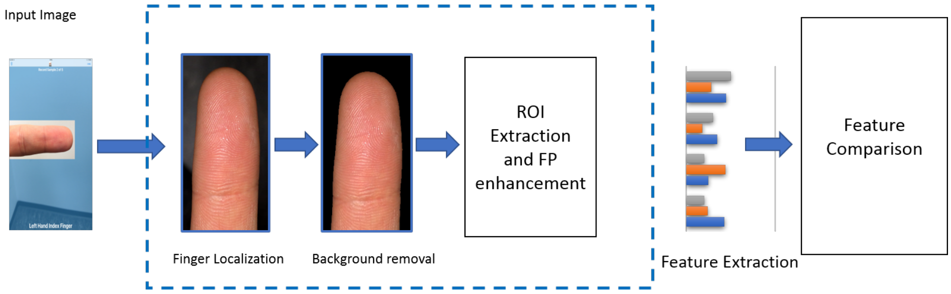


Figure 1: Block diagram of a proposed fingerphoto verification system

3 Proposed Method

This section describes a detailed overview of the proposed fingerphoto verification system. Figure 1 shows the block diagram of the proposed verification framework.

3.1 Data Capture Application

The first step in the proposed verification framework is an acquisition of the finger image also known as fingerphoto. To achieve this, we have developed an iOS mobile app which allows a user to capture the image or high-resolution videos of their fingers. The app mainly provides the capture of four fingers, i.e., left index, left middle, right index, and right middle finger. In this paper, we report the results obtained from the processing of left index finger data only. To maintain the consistency in the captured data, we display an overlay screen with ROI indication in the app and user needs to place his/her finger inside the transparent rectangular box as shown in Figure 2.a. The app also can focus on an object inside the rectangular ROI on tapping on the screen, to reduce the motion blur artifacts.

3.2 ROI extraction

Firstly, we crop the captured video frame based on the coordinates of the transparent rectangular box (See Figure 2.b). This helps us to remove most of the background information. Secondly, we apply histogram equalization to maintain uniform contrast over the cropped image. Then, to detect the finger region, we first convert the input image from RGB to L*a*b* color space also known as CIELAB or CIE L*a*b*. We then employ K-means clustering [Sp85] to partition the image colors into the foreground and background information. The output of K-means clustering is converted to a binary mask, which is then used to mask the background information from the input cropped image, the output of this stage can be seen in Figure 2.c.

Once we get the segmented image, we then crop a meaningful ROI by selecting the region inside the red bounding box shown in Figure 2.c. To obtain the bounding box, we first find out the location of the tip of the finger which is indicated by the green Point 1. We then select a suitable offset location from Point 1 and scan horizontally line by line to get the location of all remaining four points. Once we have the locations of point 2,3,4 and 5, it is very trivial to find out the bounding box specifying the ROI. The cropped output image is shown in Figure 2.d. Finally, all the cropped ROIs are re-sized to 200x500 pixel images.

3.3 Feature Enhancement

This step is based on multiscale second order local structure of an image (Hessian Matrix) to the search of tubular structures. Since the input image is of 2 dimensions, the size of the Hessian Matrix(H) will be 2x2 at a given point x_0. Therefore, upon the Eigen decomposition of the H we obtain two eigenvalues i.e., λ_1 and λ_2 such that $|\lambda_1| \leq |\lambda_2|$ is always true. As defined in[Fr98], thus for any given point x_0 the likelihood of belonging to tubular also known as vesselenss measure is given by Equation 1 [Fr98]:

$$f(x_0) = \begin{cases} 0 & if\ \lambda_2 > 0 \\ \exp\left(\frac{-\mathscr{R}_\beta^2}{2\beta^2}\right)(1-\exp\left(-\frac{S^2}{2c^2}\right)) & \end{cases} \tag{1}$$

Here $\mathscr{R}_\beta = \frac{\lambda_1}{\lambda_2}$ and S $= \sqrt{\lambda_1^2 + \lambda_2^2}$ are the blobness and second order structureness. The sensitivity of $f(x_0)$ is mainly controlled by the constants β and c. The multiscale nature of this filter is achieved by filtering the input image at different values of sigma s, the standard deviation of the second order derivatives of Gaussian. In the case of the fingerphotos, the best suitable values of β and c are found empirically as 3.0 and 1.0 respectively. Furthermore, the input image is processed using Equation 1 for multiple values of sigma s and the maximum of the output responses at each pixel is used to create the final response. The performance of such filter mainly depends on different values of sigmas. Finding out a suitable range of s is very challenging and computationally expensive task since the image needs to be filtered with different convolution kernels based on each value of s. We assume the maximum size of the diameter of the fingerprint structures to be 2 pixels wide. Hence, we used ten values of s in the range (0, 2) with the step size of 0.2. The Figure 2.e shows the output of the employed *Frangi Filter*. To verify whether the two fingerphotos are from the same subject or not, we have employed the VeryFinger SDK from Neurotechnology (COTS) [Ne] as our biometric comparator. The recommended input image resolution for VeriFinger SDK is 500 ppi (pixels per inch). Therefore, we converted the output of the *Frangi Filter* to 500 ppi using publicly available ImageMagick Library [LL]. The verification score is generated by comparing the input image against the template from the gallery.

4 Database

This section specifies the database collection and evaluation protocol. Due to the lack of the publicly available databases constructed using state-of-the-art smartphones, we created a new database we created a new database of 48 subjects. The data collection is carried out using an iPhone 6s mobile phone using a data capture application developed for the iOS environment. It is of our particular interest to use the rear-facing camera iPhone 6S which can record 1080p video at 240 fps with the flashlight turned on. We captured one-second slow motion high definition (HD) videos of the fingers of the participants. We carried out our data collection in three sessions with the gap of two weeks between each session. Out of three, first two sessions are captured for enrolment purpose with similar conditions and the third session is captured as a probe session. In all sessions, we collected two videos of fingers from each subject. In order to have enough variability in background and illumination we have captured the data in two different scenarios as 1) Indoor Scenario for Session 1, 2 with normal room light, uniform illumination and 2) Outdoor Scenario for Session 3 with the daylight/sunlight, uncontrolled environment.

Session	**No of Subjects**	**No of Videos**	**No of Frames**	**Use**	**Total Samples**
Session 1	48	2	10	Enrolment	480 frames, 96 videos
Session 2	48	2	5	Development	240 frames, 96 videos
Session 3	48	2	5	Testing	240 frames, 96 videos

Table 1: Statistics of our newly created database

The database is then further divided into development, enrolment and testing sets. The development set consists of 5 extracted video frames from the Session 2 data, and are used to determine the suitable parameters such as range of s, β and c, for the *Frangi Filter*. The output of *Frangi Filter* of 10 video frames from Session 1 data are used for the enrolment whereas five video frames Session 3 are used for the evaluation of the proposed method. In all cases, we selected every 48^{th} frame as our development, enrolment and testing data.

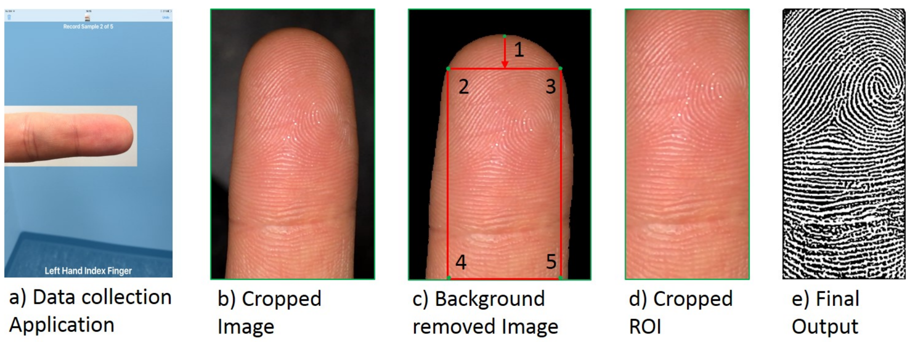


Figure 2: Screen shot of data collection application and outputs at various steps

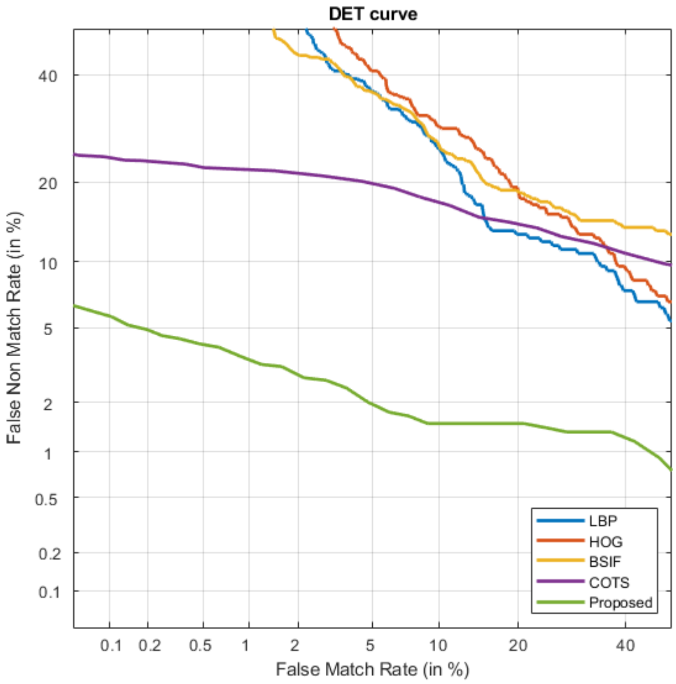


Figure 3: DET curves for best settings for standard methods, COTS with and without proposed image enhancement method

Table 1 reports the statistics of the constructed database. Note that we have only used one recorded video out of two captured recordings.

5 Experiments and Results

In this section, we discuss the results obtained using our experiments. We performed two sets of experiments to validate the effectiveness of the proposed method. The experiments resulted into 240 genuine and 11280 impostor scores for evaluation of the standard baselines. On the other hand, in the case of COTS, the experiments resulted in 1200 genuine and 56400 impostor scores. The results are presented in terms of false match rate (FMR), false non-match rate (FNMR), equal error rate (EER) and genuine match rate (GMR). Furthermore, the detection error trade-off (DET) curves are given for the graphical evaluation.

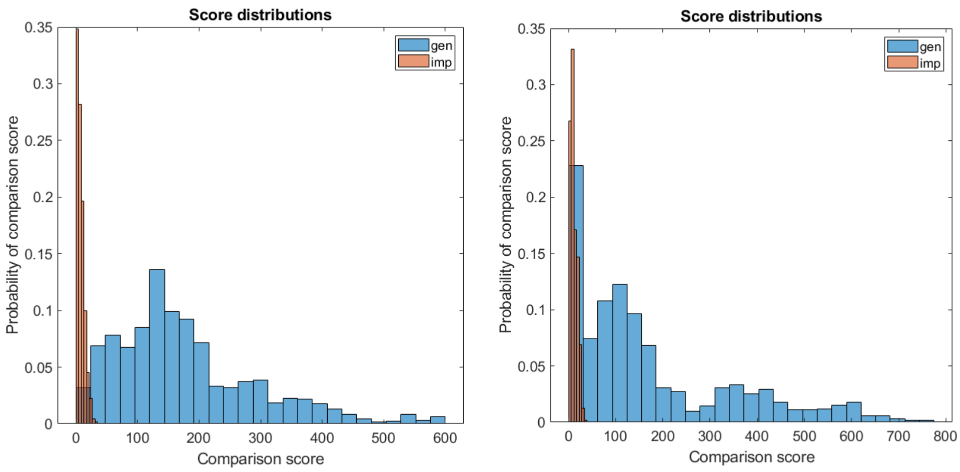
We report baseline results for the testing dataset using 1) standard methods and 2) commercial system. To obtain the results using standard methods we mainly used three well-known feature extraction techniques, i.e., Local binary pattern (LBP) [AHP06], Histogram of oriented gradients (HOG) [DT05] and Binarized statistical image features (BSIF) [KR12]. The learning of the feature vectors obtained from LBP, HOG, and BSIF on training dataset is done by the Probabilistic collaborative representation classifier (ProCRC) [Ca16]. The

ProCRC classifier mainly maximizes the joint likelihood of a test sample belonging to each class, and the sample is classified to a class with maximum likelihood. The data from Session 2 is used for development purpose, while ten frames from Session 1 videos are used to train the ProCRC classifier with 48 different classes. Finally, the verification scores are generated on the testing dataset. The EERs for the best performing settings for LBP, HOG, and BSIF are given in the Table 2.

Feature Extraction	**EER(%)**	**GMR(%)@ FMR=0.01**	**Settings**
LBP	15.23	19.58	CellSize = 8x8
HOG	19.17	16.25	CellSize = 8x8
BSIF	18.71	10.00	FilterSize= 13x13 10 Bit
COTS	14.73	75.92	Not Applicable
Proposed	**2.76**	**94.33**	Not Applicable

Table 2: EER and GMR@ FMR=0.01 values for all of the verification system

To obtain the baseline verification scores using COTS [Ne] 5 images from Session 1 are enrolled as gallery images, and the verification scores are generated using the testing set without image enhancement. From the Table 2, the performance of the COTS is significantly higher than the standard baselines in terms of GMR @ FMR = 10^{-2} which is 75.95%. However, the system could only achieve an EER of 14.73%, which is not a significant improvement over standard baselines in terms of an EER.



(a) With image enhancement

(b) Without image enhancement

Figure 4: Genuine and imposter score distributions of COTS with proposed image enhancement and without proposed image enhancement

The evaluation protocol is the same as the COTS baseline protocol. The distribution of genuine and impostor scores for the system with proposed image enhancement, without proposed image enhancement with COTS, is given in the Figure 4. The overlapping area for the system with proposed image enhancement is less than the system without image enhancement. Moreover, the false matches in the proposed system are lesser than the COTS. Roughly, 23% of the total Genuine scores are miss-classified as impostors in the case of the COTS without proposed method. The Table 2 validates these arguments in terms of EER, and the proposed system outperforms all of the baseline methods with smallest EER of 2.76% and 94.44% GMR @ FMR = 10^{-2}. Furthermore, the DET curves for best performing standard baselines, COTS without image enhancement and proposed system are given in the Figure 3, and from the figure, it is evident that the proposed method outperforms all of the other methods.

6 Conclusion

Based on the experiments and discussion we conclude that the performance of the proposed method is significantly higher than all baseline systems. This indicates that the standard methods without any pre-processing are not suitable as a fingerphoto verification system. Furthermore, we have achieved the performance of EER of 2.76% which is also higher than the state-of-the-art method proposed in [TG15] where authors have achieved the lowest EER of 3.65%. In the direction of future work, we would like to investigate the performance of the proposed method on 3D fingerprint images as well as its effectiveness for other fingerphoto databases. It could also be interesting to examine the interoperability between the fingerprint and the corresponding fingerphotos.

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