Touch-less Fingerprint Recognition System

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Abstract—**Touch-less fingerprint recognition is regarded as a viable alternative to contact-based fingerprint recognition technology. It provides a near ideal solution to the problems in terms of hygienic, maintenance and latent fingerprints. In this paper, we present a touch-less fingerprint recognition system by using a digital camera. Specifically, we address the constraints of the fingerprint images that were acquired with digital camera, such as the low contrast between the ridges and the valleys in fingerprint images, defocus and motion blurriness. The system comprises of preprocessing, feature extraction and matching stages. The proposed preprocessing stage shows the promising results in terms of segmentation, enhancement and core point detection. Feature extraction is done by Gabor filter and the favorable verification results are attained with the Support Vector Machine.**

Keywords-touch-less fingerprint recognition, preprocessing, Gabor filter, Support Vector Machine.

I. INTRODUCTION

In the past, the acquisition of fingerprint images was performed by "ink-technique" which is also referred as off-line fingerprint acquisition in the law enforcement. On the contrary, nowadays, most civil and criminal Automated Fingerprint Identification System (AFIS) has greatly benefited from the use of live-scan acquisition techniques where the existing sensors for this technique belong to one of these three families: ultrasound, optical and solid-sate. Furthermore, several companies have developed live-scan acquisition to the non-AFIS market in the last decade to provide effective solutions to the challenging problem of person recognition. Most of the sensors available today use "touch" method since it is simple and little training is required [1]. However, the touch-based electronic fingerprint scanner will lead to the weakening of durability if the device is used heavily. In addition, the pressure of the physical contacts will normally cause the touch-based fingerprint images to be degraded. On the other hand, images captured with touch-less devices are distortion free and present no deformation because these images are free from the pressure of contact. Moreover, the problems in terms of hygienic, maintenance, latent fingerprint problems and so forth are definitely overcome with the touch-less fingerprinting technology [2].

Touch-less fingerprint acquisition is a remote sensing technology to capture the ridge-valley pattern which provides essential information for recognition. Several approaches for touch-less fingerprint recognition system have been reported. In the paper [2], the authors proposed a preprocessing technique which comprised of low pass filtering, segmentation and Gabor enhancement for their own-designed touch-less sensor. [3] resolved the 3D to 2D image mapping problem that was introduced in [2] by a strong view difference image rejection method. Preprocessing of the fingerprint images captured with mobile camera has been proposed by [4]. Application of the fingerprint verification technology to mobile handsets is discussed in [5] and a novel method for the fingerprint enhancement has been developed for that particular design [5, 6]. Most recently, [7] introduced a new touch-less device - The Surround Imager™, which can acquire 3D rolled-equivalent fingerprints. To make 3D touch-less fingerprints interoperable with the current AFIS system, [8] proposed an unwrapping algorithm that unfolds the 3D touch-less fingerprint images into 2D representation that are comparable with the legacy rolled fingerprints.

In this paper, we opted for the digital camera to acquire the fingerprint images due to its affordable cost and the unique features such as zooming, auto-focusing, and high resolution that are suitable to capture high quality images. However, there are some challenging problems when developing a fingerprint recognition system that uses a digital camera. Firstly, the contrast between the ridges and the valleys in the fingerprint images obtained with a digital camera is low. Secondly, the depth of the field of the camera is small, therefore some part of the fingerprint regions are in focus but some parts are out of focus. Thirdly, motion blurriness in the images is acquired. The distinct differences of digital camera captured fingerprint image and touch-sensor acquired images can be seen in Fig. 1.

Specifically, we propose an end to end solution for the digital camera based fingerprint recognition system in which the raw images will be normalized, segmented, enhanced and followed by the core point detection. The normalized images will then be proposed by the Gabor filters and finally the matching is done by the Support Vector Machine (SVM) classifier.

The outline of the paper is as follows: Section 2 provides an overview of the proposed system and also describes the preprocessing, Gabor filter based feature extraction and fingerprint verification using SVM of the proposed system. Section 3 shows the experiment results of the preprocessing and verification. We end the paper with our conclusions.

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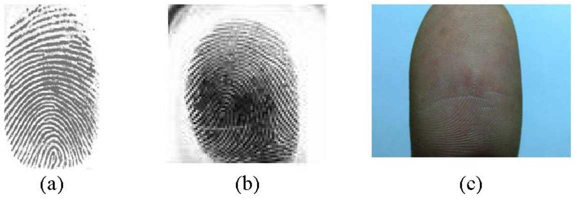

Figure 1. Fingerprint images of: (a) capasitive sensor (b) optical sensor (c) digital camera.

II. TOUCH-LESS FINGERPRINT RECOGNITION ALGORITHM

A. *Proposed System Overview*

The block diagram of the proposed touch-less fingerprint recognition system is shown in Fig.2. The main sub modules of the system comprise of:

1) *Preprocessing:* The fingerprint images are preprocessed using the proposed method which includes skin color detection, normalization, fingerprint segmentation, image enhancement and core point detection.

2) *Gabor filter based feature extraction*: The feature vectors are extracted by Gabor filter from the images after preprocessing.

3) *Fingerprint verification using SVM*: The fingerprint verification is done by using the SVM classifier.

B. *Preprocessing*

The block diagram of the proposed touch-less fingerprint recognition (Fig. 2) depicts the preprocessing steps. Firstly, we convert the RGB fingerprint image to gray scale [0-255]. We then normalize the image by changing the dynamic range of the pixel intensity values, so that the degradation that was caused by the illumination can be reduced. After the normalization, segmentation is done by the skin colour detection, adaptive thresholding and followed by the morphological processing. Then, the fingerprint image is multiplied with the binary mask obtained from the segmentation. The resulting image is cropped and enhanced by using the Short Time Fourier Transform (STFT) analysis [9]. Lastly, the core point is detected on the enhanced image. The detail description can be obtained in [10].

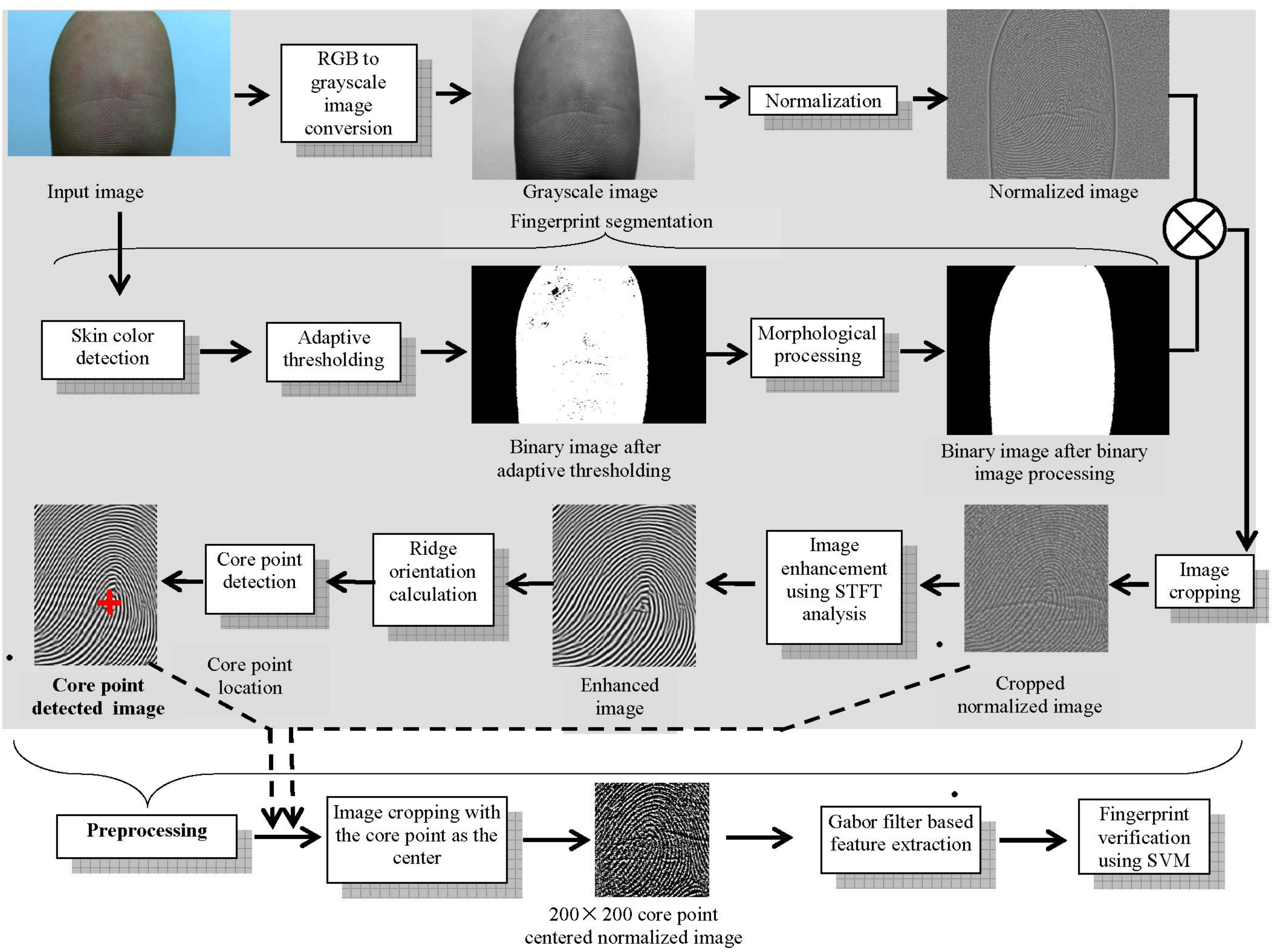

Figure 2. Block diagram of the proposed touch-less fingerprint recognition

C. Gabor Filter based Feature Extraction

We used the Gabor filter based feature extractor to form the feature vectors.

A properly tuned Gabor filters are well-known in smoothing out noise, preserving the true ridge valley structures as well as capturing both frequency and orientation information from a fingerprint image.

The general form of a 2D Gabor filter is shown below:

$$h(x,y,\theta,f,\sigma_x,\sigma_y)=\exp\left[-\frac{1}{2}\left(\frac{x'^2}{\sigma_x^2}+\frac{y'^2}{\sigma_y^2}\right)\right]\times\exp(i2\pi fx'). \quad (1)$$

$$x'=x\cos\theta+y\sin\theta,\ y'=-x\sin\theta+y\cos\theta. \quad (2)$$

where
f : the frequency of the sinusoidal plane wave,
θ : the orientation of the Gabor filter,
σ_x and σ_y : the standard deviations of the Gaussian envelope along the x and y axes, respectively.

The feature extraction method that we use here is similar to the method described in [11]. After the core point detection, the cropped normalized image from the preprocessing is cropped again into the size of 200 x 200 with the core point as the center (the core point location is determined from the preprocessing). Those images are sampled by the Gabor filters. The filtered images are divided into a set of 8 x 8 non-overlapping blocks afterward, respetively. The resulting magnitude will be then converted to a scalar number by calculating its standard deviation value. The scalar numbers form the Gabor features of each image.

In our experiment, we applied a band of 6 Gabor filters (0°, 30°, 60°, 90°, 120°, 150°), and a frequency, f = 10 which corresponds to the reciprocal of the average inter-ridge distance. Finally, $25 \times 25 \times 6$ = 3750 Gabor features are extracted from each image. To compare the features with normalization or without normalization may affect the results of the system performance, both of the features are used in the verification stage. To normalize the features, all of the features are scaled to the range of [0, 1] by

$$n=(s-m)/(M-m). \quad (3)$$

where
n : the normalized feature
s : the original feature
M : the maximum value of all features.
m : the minimum value of all features.

D. Fingerprint Verification using Support Vector Machine

SVM is a binary classifier based on the principle of structural risk minimization that maps an input sample to a high-dimensional feature space [12, 13]. In the proposed system, we adopt SVM as it could optimally separate the two classes of genuine and imposters by constructing a hyper-plane. Assume that our training dataset is denoted by $\{x_i, y_i\}, x_i \in \Re^d, y_i \in \{+1,-1\}, i=1,\cdots N$, where x_i are the extracted Gabor features belonging to either the genuine or imposter classes, y_i is the class label (+1 for genuine, -1 for imposter). The hyper-plane is defined by

$$x \cdot w + b = 0. \quad (4)$$

where
w : the normal to the plane,
b : the bias term.

To find the separating hyper-plane with the maximum distance to the closest point of the training set on each side of that plane, the square of the L2-norm of w, $\|w\|_2^2$ subject to the inequalities $(x_i \cdot w + b)y_i >= 1$ for all i is minimized [12].

The extension to non-linear boundaries can be achieved through transforming each data point to a higher dimensional space. Better separability between two classes can be achieved with a proper transformation [13]. And this transformation can be performed with the polynomial kernel as defined in (5) or the radial basis function (RBF) kernel as formulated in (6).

$$K(x_i,x_j)=(x_i \cdot x_j + 1)^n. \quad (5)$$

where
n : the order of the polynomial.

$$K(x_i,x_j)=\exp\left[-\frac{1}{2}\left(\frac{\|x_i-x_j\|}{\sigma}\right)^2\right]. \quad (6)$$

where
σ : the width of the radial basis function.

III. Experiment Evaluation

A. Image Acquisition

Since there is no standard database available for fingerprint images captured by digital camera presently, we collected the fingerprint images ourselves. The digital camera used in the image acquisition is the Canon The PowerShot Pro1, with 8 mega pixels of effective resolution and a 7x optical zoom Canon "L" series lens. The L-series lens' macro capabilities allow us to capture high resolution images while the "super macro mode" that permits close-focus to 1.2 inches enables us to get clearer foreground pattern and blurred background pattern. The setting of the digital camera is shown in Table I.

TABLE I. DIGITAL CAMERA SETTING FOR FINGERPRINT IMAGE ACQUISITION

ISO Speed	400
Image Size/ Resolution	640x480
Image Quality	Superfine
Super Macro	On
Colour Space	RGB
Drive Mode	Continuous shooting (Speed priority)

All of the fingerprint images with the size of 640x480 are acquired and collected in a closed room as shown in Fig. 3.The white static light source from the table lamp is used as it is sufficient to improve the clarity of the ridges and furrows of the captured fingerprint images. To decrease the motion blurriness, the finger is put through the hole during the image acquisition process.

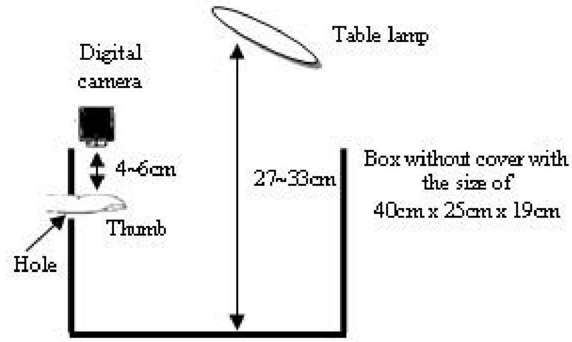

Figure 3. Experiment Setup

B. *Preprocessing Experiment Results*

Preprocessing experiments are conducted by using a total of 1938 images and the results are assessed subjectively by the visual inspection.

We observed that the proposed preprocessing provides pleasant results of the segmentation, enhancement and accurate core point detection as shown in Fig. 4. From the experiment results, it shows that this approach is able to segment and enhance most of the fingerprint images successfully as well as detect the fingerprint's core point.

By counting the number of false core point detection, it reveals that the proposed preprocessing algorithm can achieve an accuracy of 95.44% of core point detection whereas the false core point detection is only 4.56%. Defocus, motion blurriness and deep wrinkle problems are the causes of the failure of the core point detection. Fig. 5 shows some samples of the false core point detection.

C. *Verification Experiment Results*

Verification experiments are conducted by using core point centered normalized fingerprint images with the size of 200 x 200. There are 1030 fingerprint images from 103 different fingers with 10 images for each finger. After the preprocessing, the features derived from the Gabor filter based feature extractor are used for the subsequent SVM verification. For the SVM verification, we vary the number of training samples, n from 1 to 5. The remaining feature vectors, 10-n are used for testing. To enhance the reliability of the assessment, ten runs for each of n samples are performed with different

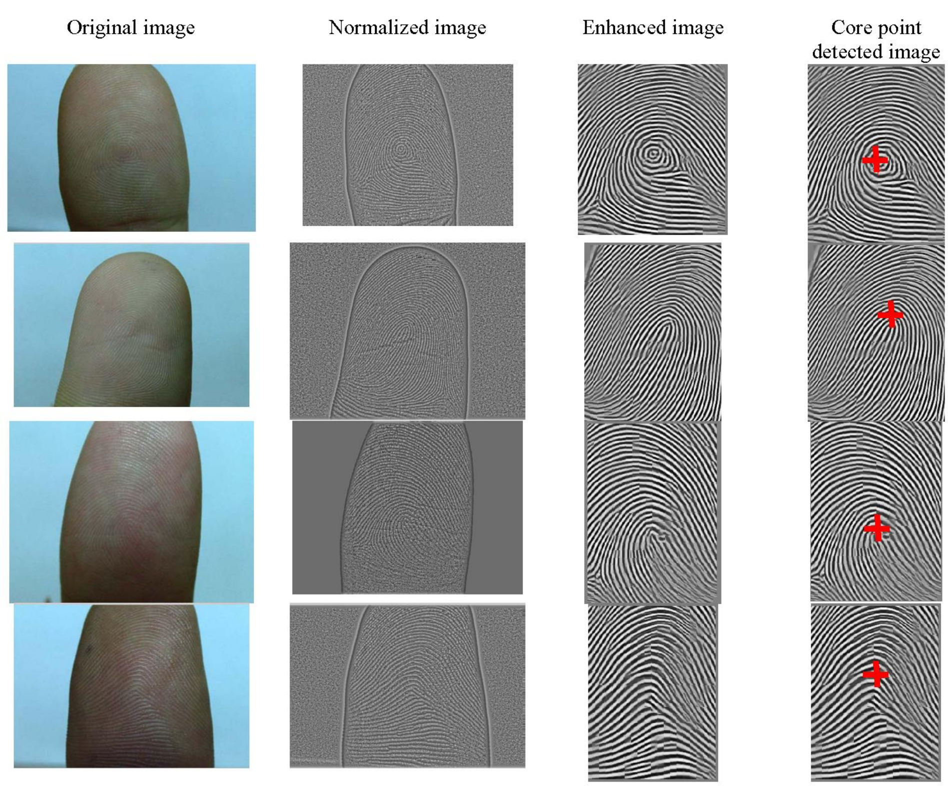

Figure 4. Results for the proposed preprocessing

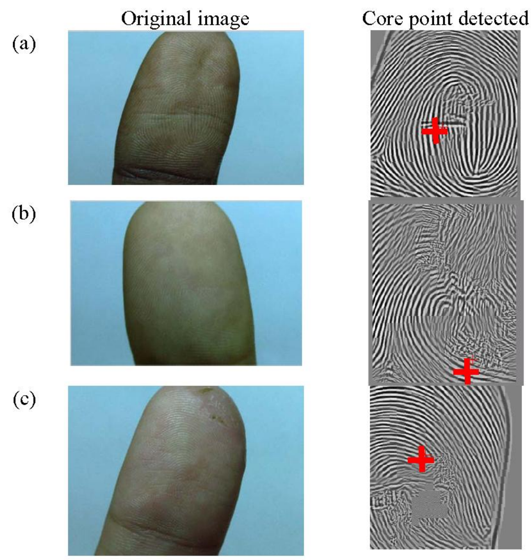

Figure 5. Samples of false core point detection using proposed preprocessing for: (a) deep wrinkle image (b) motion blurriness image (c) defocus image

random partitions between training and testing images, and the results are averaged.

Generally, there are two classes of errors in the verification system: false acceptance rate (FAR) and false reject rate (FRR). A FAR and a FRR test are performed for the performance evaluation. Our system performance is determined by using the Equal Error Rate (EER), i.e. FAR = FRR.

For the experiment evaluation using SVM classifier, the experiment setting is fixed and shown in the Table II.

In our experiment, the verification accuracy was tested using the Linear SVM, polynomial SVM and RBF SVM. The effects of the normalized and non-normalized features were also evaluated. In this study, the polynomial of degree between 2 and 4 were tested, with the best polynomial SVM result degree = 2. Thus, only the best polynomial SVM result is shown. From Fig.6 and 7, we could see that the RBF SVM is sensitive to the training data. RBF SVM could only provide pleasing results only if the features are normalized. Linear SVM and Polynomial SVM are performing well on both normalized and non-normalized features.

For the verification test on the non-normalized features, it can be seen that Linear SVM is the best while RBF SVM is the worst.

Conversely, for the verification test on the normalized features, we observe that the results of the RBF SVM and Linear SVM are compatible satisfying whereas Polynomial SVM is the worst. Although RBF SVM could perform well here, it is unfortunately limited by the computation cost and takes the longest processing time in both training and testing.

TABLE II. CONFIGURATION FOR THE EXPERIMENTS

Setting	***Training Images,n**	**Testing Images,10-n**	**No. of Client**	**No. of Imposter**
1	1	9	9x103 =927	9x103x102 =94554
2	2	8	8x103 =824	8x103x102 =84048
3	3	7	7x103 =721	7x103x102 =73542
4	4	6	6x103 =618	6x103x102 =63036
5	5	5	5x103 =515	5x103x102 =52530
*Number of training images that used in SVM classifier.				

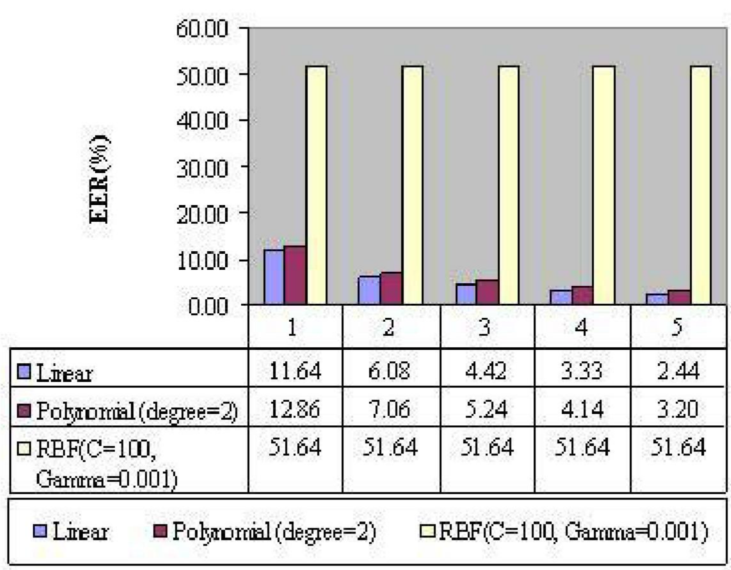

Figure 6. Results of the SVM with non-normalized features

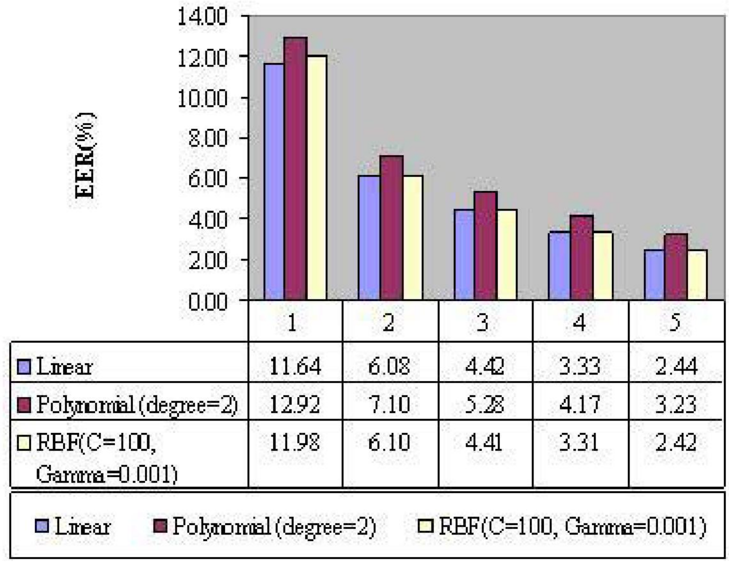

Figure 7. Results of the SVM with normalized features

IV. CONCLUSIONS

In this paper, we have presented a touch-less fingerprint recognition system. The experiment results signified an improvement using the proposed algorithm in the segmentation, enhancement and core point detection for the fingerprint images captured by the digital camera. Moreover, it has also presented an effective verification technique that employs the SVM where feature vectors are extracted using the Gabor filter.

REFERENCES

[1] D. Maltoni, D. Maio, A. K.Jain, and S. Prabhakar, Handbook of Fingerprint Recognition, Springer- Verlag, New York, 2003.

[2] Y. Song, C. Lee, and J. Kim, "A New Scheme for Touchless Fingerprint Recognition System", International Symposium on Intelligent Signal Processing and Communication Systems, Korea, 2004.

[3] C. Lee, S. Lee, and J. Kim, "A Study of Touchless Fingerprint Recognition System", Joint IAPR International Workshops, SSPR 2006 and SPR 2006, Hong Kong, China, 2006.

[4] C. Lee, S. Lee, J. Kim, and S. Kim, "Preprocessing of a Fingerprint Image Captured with a Mobile Camera ", Advances in Biometrics: International Conference, Hong Kong, China, 2006.

[5] M. Hashimoto, S. Tanaka, and J. Thornton, "Biometrics in Mobile Handsets", Technical Report, Mitsubishi Electric Corporation, June 2005.

[6] T. Nakamura, H. Fujiwara, M. Hirooka, and K. Sumi, "Fingerprint Enhancement Using a Parallel Ridge Filter", 17th International Conference on Pattern Recognition 2004, Cambridge, United Kingdom, 2004.

[7] G. Parziale and E. Diaz-Santana, "The Surround Imager: A Multi-camera Touchless Device to Acquire 3D Rolled-Equivalent Fingerprints", IAPR International Conference on Biometrics, Hong Kong, China, 2006.

[8] Y. Chen, G. Parziale, E. Diaz-Santana, and A. Jain, "3D Touchless Fingerprints: Compatibility with Legacy Rolled Images", Proceeding of Biometric Symposium, Biometric Consortium Conference, Baltimore, MD, U.S.A, 2006.

[9] S. Chikkerur, A.C., and V. Govindaraju, "Fingerprint Image Enhancement Using STFT Analysis", International Conference on Advances in Pattern Recognition, United Kingdom, 2005.

[10] B.Y. Hiew, Andrew B.J. Teoh, and David C.L. Ngo, "Preprocessing of Fingerprint Images Captured with a Digital Camera", 9th International Conference on Control, Automation, Robotics and Vision (ICARCV 2006), Singapore, 2006.

[11] C.J. Lee and S.D. Wang, "Fingerprint feature extraction using Gabor filters", Electronics Letters, vol.35, no.4, 1999, pp. 288-290

[12] Y.Y. Chen and S.H. Lai, "Audio-visual information fusion for SVM-based biometric verification", The 9th IEEE International Workshop on Cellular Neural Networks and their Applications, Hsin-chu, Taiwan 2005.

[13] Burges, C.J.C., "A Tutorial on Support Vector Machines for Pattern Recognition", Knowledge Discovery and Data Mining, vol.2, no.2, 1998, pp. 121-167.