ISSN: 0976-9102 (ONLINE)
DOI: 10.21917/ijivp.2020.0303

A NOVEL SYSTEM BASED ON PHASE CONGRUENCY AND GABOR - FILTER BANK FOR FINGER KNUCKLE PATTERN AUTHENTICATION

Rabah Hammouche[1], Abdelouahab Attia[2] and Samir Akrouf[3]
[1]*Department of Computer Science, Mohamed El Bachir El Ibrahimi University, Algeria*
[2]*LMSE Laboratory, Mohamed El Bachir El Ibrahimi University, Algeria*
[3]*Department of Computer Science, Mohamed Boudiaf University, Algeria*

Abstract

The authentication of individuals based on Finger Knuckle print (FKP) is a very interesting system in the biometric community. In this paper, we introduce a biometric authentication system based on the FKP trait which consists of four stages. The first one is the extraction of the Region of Interest (ROI). The Phase Congruency method with Gabor filters bank descriptors has been used in the feature extraction stage. Then to enhance the performance of the proposed scheme the Principle Component Analysis (PCA) + Linear Discriminant Analysis (LDA) method has been used in the dimensionality reduction stage. Finally, cosine Mahalanobis distance has been used in the matching stage. Experiments were conducted on the FKP PolyU Database which are publicly available. The reported results with comparison to previous methods prove the effectiveness of the proposed scheme, as well as the given system can achieve very high performance in both the identification and verification modes.

Keywords:

Finger Knuckle Print, Phase Congruency, Gabor Filters Bank, Score-Level-Fusion

1. INTRODUCTION

In the recent years, biometric authentication is preferred over the traditional methods due to its stability and efficiency that are powered by its faculty to capture the physiological and behavioral characteristics of persons through their face, iris, fingerprint, palm print, finger knuckle print, etc. [1] Among these characteristics, this paper investigates Finger Knuckle Print (FKP) exhaustively. FKP comprises of the textures and lines around the phalangeal joint on the outer surface of finger knuckle. These textures and lines vary for each individual can used to differentiate one form the other. FKP has some advantages [2] such as:

- The easy and cost efficient image acquisition,
- FKP based access systems are very suitable for indoor and outdoor usage and can be used under extreme weather and illumination conditions.
- FKP features known by its stability over time.

Thus, FKP based biometric identification is very consistent and it can successfully differentiate people from different population [3] - [5]. In the case that we have studied in this paper, a novel descriptor based on Phase Congruency and Gabor filter bank is considered for FKP authentication system denoted as PC-Gabor, which is elaborated in section 3.

The rest of this paper is organized as follows: section 2 describes the literature overview on the FKP recognition system and section 3 presents the methodology for the FKP authentication system based on the PC-Gabor descriptor. The section 4 presents the experimental results. The conclusions and future work are given in the last section.

2. LITERATURE OVERVIEW

A considerable amount of literature has been published on biometric systems based FKP recognition. However, Jaswal et al. [6] have presented a recognition system based on finger dorsal surface. Initially the images acquired are preprocessed by median filter. Subsequently, the Scale Invariant Feature Transform (SIFT) and PCA based LDA methods are combined for feature extraction. Later, the resultant vectors of the feature are classified and recognized using nearest neighbor classifier (KNN) based on three distance measures, namely Euclidean Distance, Spearman Correlation Coefficient, and City Block Distance.

Waghode et al. [7] have proposed a scheme for an FKP recognition system by using subspace techniques. Initially, the Gabor filter has been used to remove noise. Then, for feature extraction, PCA is used. Finally, LDA and Probabilistic Neural Network (P-NN) classifiers have been employed for the matching stage.

Aoyama et al. [3] have introduced an algorithm for person recognition based FKP image using Band Limited Phase Only Correlation (BLPOC) based local block matching. The system begins with applying the 2D Discrete Fourier Transform (DFT) to generate the phase information, which is followed by the phase-based correspondence matching. Finally, the BLPOC-based local block matching is used by employing the global and local representation of FKP images to calculate the matching score.

Nigam et al. [8] have investigated an FKP recognition system based on concatenating multiple texture features. However, the FKP image is processed and then the curvature Gabor filter is used to extract the Region of Interest (ROI). After that, for enhancement of ROI, the Gradient-Based Ordinal Relationships are used to obtain robust image representation. Finally, for the matching step the Dissimilarity Incorrectly Tracked Corners (ITC) measure is applied.

Nunsong et al. [9] have introduced an FKP recognition system using Fractal Dimension based on Gabor Wavelet (FDGW) descriptor. Firstly, Gabor Wavelet is used to extract features. After that the Fractal Dimension which shows improvement by classifying the under-counting and over-counting problems is applied to the FKP features.

Kim et al. [10] have proposed a new method which extracts line features from the FKP image. First, the horizontal and the vertical knuckle lines are extracted using Shift-and-Difference matrix which is activated using the Sigmoid function for contract enhancement. After that, a Fourier spectrum analysis is employed to extract line features. Finally, the two-directional line features are concatenated at the score level using Total Error Rate Minimization that Adopts the Extreme Learning Machine Kernel (TERELM).

Muthukumar et al. [11] have introduced an FKP biometric system using the Short and Long Gabor features. For the matching phase, the Hamming Distance (HD) and Support Vector Machines (SVM) are used. Finally, the scores of both methods are fused and used to determine the identity of individual.

Zhai et al. [5] have proposed an FKP recognition system using Batch Normalized Convolutional Neural Network (CNN) architecture with histogram equalization for data augmentation.

Attia et al. [4] have proposed an FKP recognition system using Multi-Scale Bank of Binearized Statistical Image Features (B-BSIF). This system extract features to encode FKP traits using Different Best Performing Convolution Filters. After that the encoded FKP images was used to extract histograms which are concatenated to obtain a large feature vector, then for dimensionality reduction. PCA+LDA technique has been applied, for identification, and the nearest neighbor classifier is used.

Chaa et al. [12] have introduced a new method that merges two histograms of oriented gradients (HOG) from reflectance and illumination. FKP images are extracted by the Adaptive Single Scale Retinex (ASSR) algorithm, to obtain a huge feature vector. The PCA +LDA technique has been applied for dimensionality reduction. Finally, for classification, cosine distance is used.

Attia et al. [13] have presented an FKP recognition system based on feature level fusion of imaginary and real image extracted by 1D Log Gabor filter. Then they extract the feature vectors of both images by applying Three Patch Local Binary Patterns (TPLBP). All the feature vectors thus extracted are concatenated to form one feature vector. Later, LDA is used for dimensionality reduction. Finally, cosine Mahalanobis is used for matching the nearest neighbor classifier.

Rachid et al. [14] have presented a multimodal system based on the FKP image. The Principal Component Analysis Network (PCANet), a simple Deep learning method, has been used. The PCANet treats an FKP image by two stages that involve filter banks and a simple binary hashing and block histogram for clustering of feature vectors. Then, the classification by linear multiclass Support Vector Machine (SVM) is applied.

3. PROPOSED METHOD

The Fig.1 illustrate the block diagram of the proposed FKP based individual recognition system based on the PC-Gabor descriptor. The FKP traits of an individual are recorded and preprocessed to extract regions of interest (ROI). After that the features are extracted by using both PC and Gabor descriptors methods. Then, these features are followed by sub projection to reduce dimensionality by applying the PCA + LDA technique to obtain the relevant feature's representation. The consist features template is saved in the database. In the test stage, the FKP traits of users follow the same process mentioned above and compared to the stored templates in the database to determine the identity of a person. Each stage of the block diagram is described in the following sections:

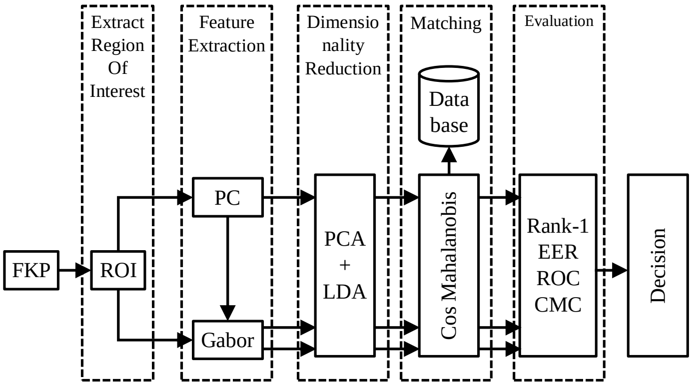


Fig.1. Proposed Scheme

3.1 DATABASE

The extensive experiments of this paper are tested on the PolyU FKP database [15]. This database contains 7920 images collected from 165 subjects (125 males and 40 females). Among them, 143 people are aged between 20 and 30 years while the others are aged between 30 and 50 years. All images are collected in two separate sessions, where each person provides 48 different FKP images, 24 for each session collected from four fingers types: Left Index Finger (LIF), Right Index Finger (RIF), Left Middle Finger (LMF) and Right Middle Finger (RMF), wherein for each finger type there are 6 images.

3.2 ROI EXTRACTION

The extraction of the region of interest (ROI) is based on determining the local coordinate system. The main steps for processing ROI are detailed as follows:

First, a Gaussian smoothing applied to the original image. Then the smoothed image is down-sampled to 150 dpi (Dots Per Inch). Secondly, a Canny edge detector is used to extract the bottom boundary of the finger, and the bottom boundary is fitted to determinate the X-axis of the coordinate system. Thirdly, the Y-axis of the coordinate system is determined by cropping a sub-image from the original image. Subsequently, a canny edge detector is applied to the cropped sub-image, followed by the application of the convex direction coding scheme. Finally, by using the X-axis and Y-axis the local coordinate system is determined, and the ROI can be extracted with a fixed size. [2] The Fig.2 illustrates the main steps of ROI extraction process.

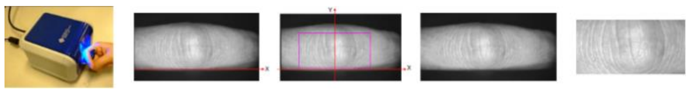


Fig.2. Process of ROI extraction Image

3.3 FEATURE EXTRACTION

Feature extraction until now is an important step in the machine learning system including biometrics. There are different kinds of feature descriptors in the literature. However, in this paper, we focus on the Phase Congruency and Gabor filter bank descriptors. These two methods are combined together for extracting the concise features.

3.3.1 Phase Congruency:

Rather than considering that, the image should be compressed into a set of contours. Thus the detection of features by PC considers that the image should be high in information and low in redundancy. This model looks like patterns of order in the phase component of the Fourier transform and postulates that features are as points in an image having high phase order [16].

In practice the study of Local Energy (LE) is used for image contours detection. In these contours, the Phase congruency and the Local energy are maximum. In fact, the LE is equal to the PC, weighted by the sum of amplitudes of Fourier.

Given a one-dimensional signal $F(x)$, its Fourier series expansion [17]:

$$F(x) = \sum_n A_n \cos(nwx + \varnothing_n) \tag{1}$$

where, A_n and $\varnothing_n$ represents respectively the amplitude and the phase of the n^{th} Fourier components, and w is a constant (usually 2π).

The phase congruency function is defined as:

$$PC(x) = \frac{|E(x)|}{\sum_n A_n(x)} \tag{2}$$

The local energy function $E(x)$ can be defined as (reference)

$$E(x) = \sqrt{F^2(x) + H^2(x)} \tag{3}$$

where $H(x)$ is the 90° phase shift of $F(x)$ (Hilbert Transform)

$$H(x) = -\sum_n A_n \sin(nwx + \varnothing_n) \tag{4}$$

Then

$$E(x) = \sqrt{\left[A_n \cos(nwx + \varnothing_n)\right]^2 + \left[A_n \sin(nwx + \varnothing_n)\right]^2} \tag{5}$$

Alternatively, local energy can be expressed by

$$E(x) = \sum_n A_n \cos(nwx + \varnothing_n - \theta) \tag{6}$$

where,

$$\theta = \tan^{-1}\left(\frac{\sum_n A_n \sin(nwx + \varnothing_n)}{\sum_n A_n \cos(nwx + \varnothing_n)}\right) \tag{7}$$

The value of θ that maximizes the local energy is the weighted mean phase angle of all the Fourier terms.

3.4 GABOR FILTER

Gabor filters have been widely used to extract features from biometric images, both spatial and frequency information can be extracted by this filter [18]. The Gabor filter creates three types of features magnitude, phase, and orientation [19]. These filters are a Gaussian envelope modulated by a sinusoidal plane wave. The Gabor filter can be defined in the spatial domain as follows [20]:

$$\psi(x,y) = \frac{f_u^2}{\pi k \eta} e^{\left(\left(\frac{f_u^2}{k^2}\right)x'^2 + \left(\frac{f_u^2}{\eta^2}\right)y'^2\right)} e^{j2\pi f_u x'} \tag{8}$$

where

$$x' = x\cos\theta_v + y\sin\theta_v \tag{9}$$

$$y' = -x\sin\theta_v + y\cos\theta_v \tag{10}$$

$$f_u = f_{max}/2^{(u/2)} \tag{11}$$

$$\theta_v = v\pi/8 \tag{12}$$

where, f_u and θ_v present respectively the center frequency and orientation. ($f_{max} = 0.25$). k and η determine the ratio between the center frequency and the size of the Gaussian envelope where the most common parameters used are $k = \eta = \sqrt{2}$ [20].

In this paper, for extracting different features of images we used a bank featuring filters of five scales and eight orientations, $u = 0,1,...,4$ and $v = 0,1,...,7$.

Let $I(x,y)$ a grey-scale FKP image, where the procedure of features extraction can be defined as :

$$G_{u,v}(x,y) = I(x,y) * \psi_{u,v}(x,y) \tag{13}$$

where, $G_{u,v}(x,y)$ are the complex filtering output

The Fig.3 illustrates a sample of feature extraction based PC-Gabor method.

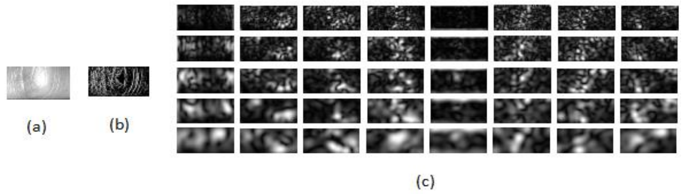


Fig.3. (a) FKP image, (b) PC Image, (c) Gabor filters responses

3.5 DIMENSIONALITY REDUCTION

The extracted features obtained from PC and Gabor filter have high dimension and it is hard to evaluate them. It is suitable to decrease the dimension of feature vectors using Principle Component Analysis (PCA) [21] which is the most popular method for dimensionality reduction. But, in PCA the possibility of separation between classes is ignored. For that purpose, the Linear Discriminant Analysis (LDA) [22] can be used to avoid PCA's issue.

In this paper, PCA + LDA has been adapted, where PCA is used firstly then LDA is applied on the PCA weights.

4. EXPERIMENTS

In this section, we reported an experimental evaluation of the introduced FKP recognition system based on PC and Gabor filters bank.

4.1 EXPERIMENTAL EVALUATION PROTOCOLS

The performance of the biometric system is analyzed for both modes of verification and identification. For verification mode, the system is evaluated by the Receiver Operating Characteristics (ROC) curve which is a plot of False acceptance rate (FAR) against False rejection rate (FRR) for various threshold values and by the Equal Error Rate (EER) that is defined as the error rate where the value of FAR and FRR are the same.

For identification mode, the system is evaluated by the Cumulative match curves (CMC) which is a plot of a probability of identification against the size of the enrolled users and also evaluated by the Recognition rate (Rank-1) that is given by,

$$\text{Rank-1} = \frac{M}{N} \times 100\% \tag{14}$$

where, M is the number of images assigned to the right identity, N is the total number of images of identification attempts.

4.2 EXPERIMENTAL RESULTS

In this section, we report two different experiments, the first one is for the unimodal system. Thus both methods PC and Gabor are applied separately on the FKP image, and then, the Gabor filter bank is used on PC images (PC-Gabor). The second experiment presents a multi-biometric FKP recognition system, where the PC-Gabor is used. These experiments are based on score level fusion. Thus, the min, sum and sum-weighted rules are employed.

4.2.1 Experiment 1 (Unimodal System):

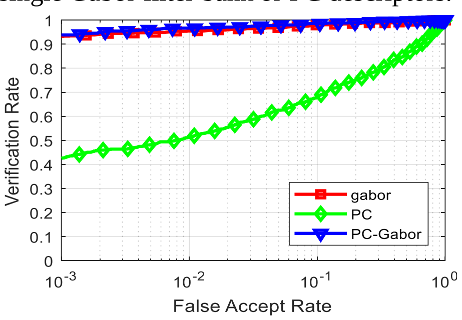
First, we test each descriptor separately (PC, Gabor), then to extract PC-Gabor features we apply Gabor on the PC image obtained from the PC method. Here the modality (LIF, RIF, LMF, and RMF) was used separately. The Table.1 shows the results of both modes of identification and authentication using the Rank-1 and the EER of each test for each finger, respectively.

Table.1. Rank-1 (%) and EER (%) obtained from a different type of finger

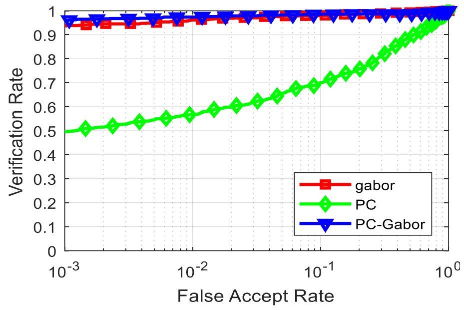
FKP Traits	Identification			Authentication		
	Rank-1 (%)			EER (%)		
	PC (%)	Gabor (%)	PC-Gabor (%)	PC (%)	Gabor (%)	PC-Gabor (%)
LIF	45.76	93.03	93.64	23.29	3.54	2.83
RIF	45.76	93.23	92.73	23.63	3.95	3.10
LMF	52.32	93.33	95.66	22.85	2.93	2.12
RMF	49.39	91.31	93.43	19.81	2.94	3.03

From Table.1, it is clear that better performance is obtained by the PC-Gabor descriptor. However, we can observe that the LMF finger is an identification system that can achieve a Rank-1 of 95.66%. In the case of using LIF finger, Rank-1 is 93.64% also for RMF finger, Rank-1 achieves 93.43% and finally the Rank-1 for RIF finger is equal to 92.73%.

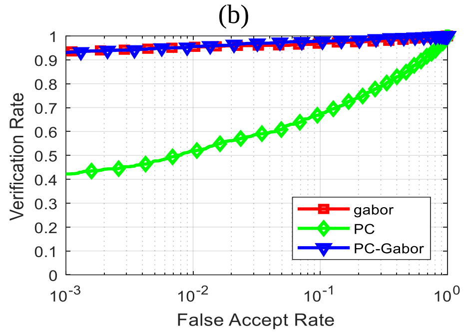
The PC, Gabor, and PC-Gabor comparison results for the different modality are presented in terms of CMC, ROC and EER curves, which can be seen in Fig.4, Fig.5 and Fig.6. These plots demonstrate that the use of PC-Gabor is a powerful descriptor than using single Gabor filter bank or PC descriptors.



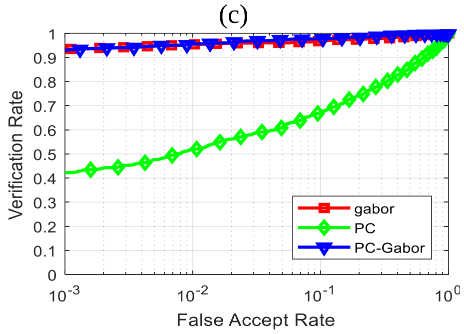
(a)



(b)

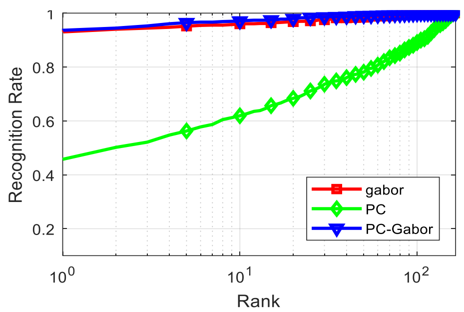


(c)

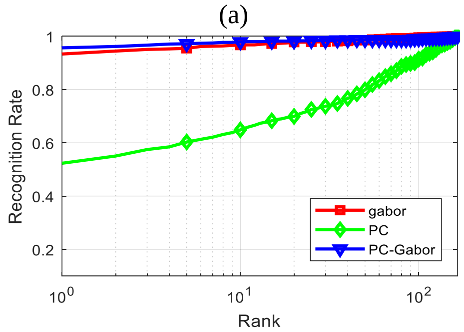


(d)

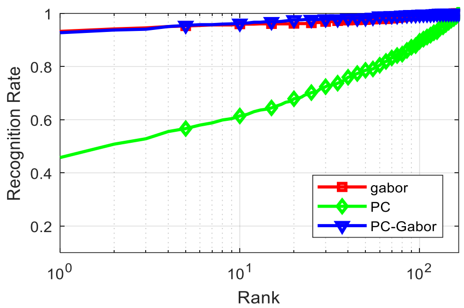
Fig.4. ROC curve for all modalities (a) LIF, (b) LMF, (c) RIF, (d) RMF



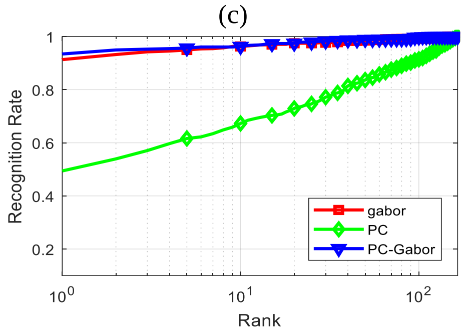
(a)



(b)

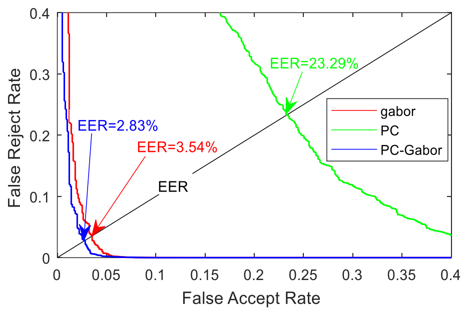


(c)

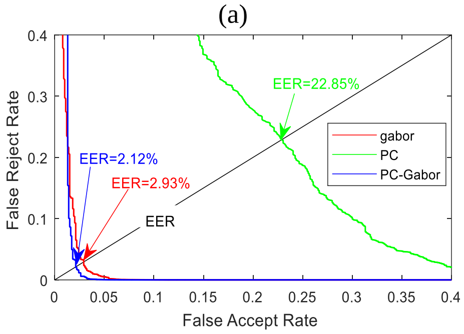


(d)

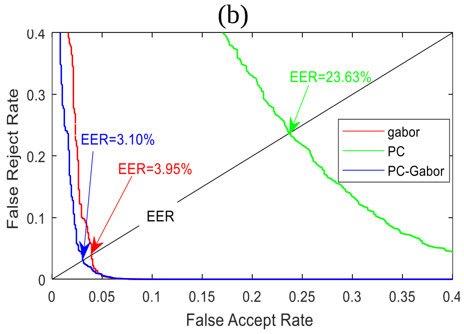
Fig.5. CMC curve for all modalities (a) LIF, (b) LMF, (c) RIF, (d) RMF



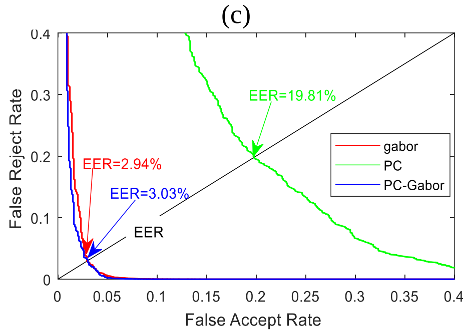
(a)



(b)



(c)



(d)

Fig.6. EER curve for all modalities (a) LIF, (b) LMF, (c) RIF, (d) RMF

To further express the effectiveness of the proposed system based on the PC-Gabor descriptor, the comparison is done with some works of literature on individual FKP traits as presented in Table.2. However, we can see that accomplished acceptable results in terms of Rank-1 with low EER.

4.2.2 Experiment 2 (Multimodal System):

Our aim for this experiment is to study the performance of the system, FKP recognition, using PC-Gabor technique in the case of information fusion. Multimodal systems fusing information from different sources might have some limitations including accuracy and noise of the unimodal systems. Hence, further tests are carried out. For that, we consider different scenarios where the information presented by the four-finger types (LIF, LMF, RIF, and RMF) modality is included.

However, in this tests the score level fusion is used where the information is fused by applying three rules which are: min rule, sum rule, and sum-weighted rule (SUM_W). Therefore, three possibilities of combining the fingers were considered (two fingers, three fingers and four fingers). Consequently, the Table.3 illustrates the score of two fingers while the three fingers and four fingers are presented by Table.4.

From Table.3 and Table.4, we can perceive that the multimodal system achieves better performance than the unimodal system in terms of Rank-1 and EER. For example, by using just LMF modality the system can achieve a Rank-1 of 95.66% with EER equal to 2.12%. But, the multimodal system achieves a Rank-1 of 99.19%, 99.6%, 100% and an EER of 0.3%, 0.1%, 0%, respectively for RIF-RMF, LIF-RIF-RMF and all fingers.

Table.2. Comparative for a Single Modal System

Methods	LIF		LMF		RIF		RMF	
	Rank-1 (%)	EER (%)	Rank-1 (%)	EER (%)	Rank-1 (%)	EER (%)	Rank-1 (%)	EER (%)
RBF classifier [14]	90.90	-	94.41	-	85.25	-	88.28	-
RFT classifier [14]	89.42	-	91.78	-	91.91	-	92.12	-
SVM classifier [14]	95.75	-	97.30	-	96.83	-	95.15	-
Euclidean Distance [6]	-	-	82.456	-	-	-	81.783	-
Spearman Correlation [6]	-	-	96.890	-	-	-	97.10	-
City Block [6]	-	-	79.507	-	-	-	79.44	-
ASSR+HOG+LDA [12]	94.85	-	94.85	-	91.41	-	91.82	-
v_{code}^{GORP} [8]	97.2727	3.297	97.5978	3.0303	97.8285	2.8282	97.6092	3.2496
h_{code}^{GORP} [8]	94.7770	6.869	95.1156	6.3289	94.7995	7.1244	94.8332	6.9324
h_{code}^{SGORP} [8]	97.0546	4.066	97.6070	3.1132	97.0794	3.9551	97.1706	3.7173
v_{code}^{SGORP} [8]	97.5353	3.2988	98.1309	2.2895	97.8734	3.0302	97.4697	3.7052
Directional Filter Bank (DFB) + LDA [23]	88.68	-	90.30	-	89.79	-	89.79	-
Multi-Scale Shift Local Binary Pattern (MSLBP) + PCA + LDA [24]	93.80	-	94.70	-	92.20	-	94.84	-
Gabor+DBC [25]	89.91	-	91.03	-	89.12	-	90.82	-
Gabor+ITBC-DBC [25]	90.12	-	92.33	-	90.42	-	91.33	-
Gabor+MDBC [25]	91.51	-	93.13	-	92.91	-	93.73	-
Proposed Method	93.64	2.83	95.66	2.12	92.73	3.10	93.43	3.03

Table.3. Rank-1 (%) and EER (%) obtained by fusion of two types of finger

Rule	Rank-1/ EER (in %)	The fusion of two types of finger					
		LIF-LMF	LIF-RIF	LIF-RMF	LMF-RIF	LMF-RMF	RIF-RMF
SUM	Rank-1	98.79	98.38	98.89	98.79	99.29	99.19
	EER	0.81	1.01	0.40	0.70	0.38	0.30
MIN	Rank-1	98.69	98.69	99.09	98.79	99.09	99.19
	EER	0.91	1.11	0.48	0.61	0.50	0.30
SUM_W	Rank-1	98.79	98.38	98.89	98.89	98.89	99.19
	EER	0.81	1.01	0.40	0.71	0.41	0.30

Table.4. Rank-1 (%) and EER (%) obtained by fusion of three and all type of finger

Rule	Rank-1/ EER (%)	The fusion of three and four types of finger				
		LIF-LMF-RIF	LIF-LMF-RMF	LIF-RIF-RMF	LMF-RIF-RMF	LIF-LMF-RIF-RMF
SUM	Rank-1	99.60	99.60	99.60	100.00	100.00
	EER	0.30	0.10	0.10	0.00	0.00
MIN	Rank-1	99.49	100.00	99.70	99.90	100.00
	EER	0.40	0.08	0.12	0.10	0.01
SUM_W	Rank-1	99.60	99.60	99.60	100.00	100.00
	EER	0.20	0.20	0.10	0.00	0.01

The Table.5 shows the comparison of proposed multimodal system with existing multimodal systems. We can notice in Table.5 that the proposed system under verification mode attained the lowest EER (%) compared to EER (%) by systems in [8] and [23]. In identification mode, the proposed system achieved highest recognition rate compared to works [12] and [23].

5. CONCLUSION

In this work, the phase congruency with Gabor filter bank has been investigated and applied to FKP traits. First, the features are extracted by PC-Gabor. Then the PCA+LDA method has been used to reduce these large features vector. The matching process was done by using the KNN classifier which uses the cosine Mahalanobis distance. The evaluation of the proposed system on FKP PloyU dataset demonstrates the efficiency and robustness of proposed person authentication based on PC-Gabor. Besides, several experiments using multiple fingers were accomplished and reported. Especially, in this case of multimodal, where the rank-1 with EER is achieved, is able to compete with existing systems and give good results. The future work aims to integrate other modalities, such as face, to take advantage of the modalities for improving the study security system and achieving high accuracy.

REFERENCES

[1] O.S. Adeoye, "A Survey of Emerging Biometric Technologies", *International Journal of Computer Applications*, Vol. 9, No. 10, pp. 1-5, 2010.

[2] L. Zhang, L. Zhang, D. Zhang and H. Zhu, "Online Finger-Knuckle-Print Verification for Personal Authentication", *Pattern Recognition*, Vol. 43, No. 7, pp. 2560-2571, 2010.

[3] S. Aoyama, K. Ito and T. Aoki, "A Finger-Knuckle-Print Recognition Algorithm using Phase-Based Local Block Matching", *Information Sciences*, Vol. 268, No. 5, pp. 53-64, 2014.

[4] A. Attia, M. Chaa, Z. Akhtar, and Y. Chahir, "Finger Kunckcle Patterns based Person Recognition Via bank of Multi-Scale Binarized Statistical Texture Features", *Evolving Systems*, Vol. 9, No. 1, pp. 1-11, 2018.

[5] Y. Zhai, H. Cao and L. Cao, "A Novel Finger-Knuckle-Print Recognition based on Batch-Normalized CNN", *Proceedings of Chinese Conference on Biometric Recognition*, pp. 11-21, 2018

[6] G. Jaswal, R. Nath and A. Kaul, "FKP based Personal Authentication using SIFT Features Extracted from PIP Joint", *Proceedings of 3rd International Conference on Image Information Processing*, pp. 214-219, 2015.

[7] A.B. Waghode and C.A. Manjare, "Biometric Authentication of Person using Finger Knuckle", *Proceedings of International Conference on Computing, Communication, Control and Automation*, pp. 1-6, 2017.

[8] A. Nigam, K. Tiwari and P. Gupta, "Multiple Texture Information Fusion for Finger-Knuckle-Print Authentication System", *Neurocomputing*, Vol. 188, pp. 190-205, 2016.

[9] W. Nunsong and K. Woraratpanya, "An Improved Finger-Knuckle-Print Recognition using Fractal Dimension based on Gabor Wavelet", *Proceedings of International Conference on International Joint Conference on Computer Science and Software Engineering*, pp. 1-5, 2016.

[10] J. Kim, K. Oh, B.S. Oh, Z. Lin and K.A. Toh, "A Line Feature Extraction Method for Finger-Knuckle-Print Verification", *Cognitive Computation*, Vol. 11, No. 1, pp. 50-70, 2019.

[11] A. Muthukumar and A. Kavipriya, "A Biometric System based on Gabor Feature Extraction with SVM Classifier for Finger-Knuckle-Print", *Pattern Recognition Letters*, Vol. 125, pp. 150-156, 2019.

[12] M. Chaa, N.E. Boukezzoula and A. Meraoumia, "Features-Level Fusion of Reflectance and Illumination Images in Finger-Knuckle-Print Identification System", *International Journal of Artificial Intelligence Tools*, Vol. 27, No. 03, pp. 1850-1857, 2018.

[13] A. Attia, A. Moussaoui, M. Chaa and Y. Chahir, "Finger-Knuckle-Print Recognition System based on Features-Level Fusion of Real and Imaginary Images", *ICTACT Journal on Image and Video Processing*, Vol. 8, No. 4, pp. 1793-1799, 2018.

[14] R. Chlaoua, A. Meraoumia, K.E. Aiadi and M. Korichi, "Deep Learning for Finger-Knuckle-Print Identification System based on PCANet and SVM Classifier", *Evolving Systems*, Vol. 10, No. 2, pp. 261-272, 2019.

[15] D.R. Arun, C.C. Columbus and K. Meena, "Local Binary Patterns and Its Variants for Finger Knuckle Print Recognition in Multi-Resolution Domain", *Circuits and Systems*, Vol. 7, No. 10, pp. 1-13, 2010.

[16] M. Concetta Morrone and D.C. Burr, "Feature Detection in Human Vision: A Phase-Dependent Energy Model", *Proceedings of the Royal Society B*, Vol. 235, No. 1280, pp. 221-245, 1988.

[17] P. Kovesi, "Image Features from Phase Congruency", Technical Report, Department of Computer Science, The University of Western Australia, pp. 1-26, 1999.

[18] D. Gabor, "Theory of Communication. Part 1: The Analysis of Information", *Journal of the Institute of Electrical Engineers-Part III Radio and Communication Engineering*, Vol. 93, No. 26, pp. 429-441, 1946.

[19] A. Kong, "An Evaluation of Gabor Orientation as a Feature for Face Recognition", *Proceedings of 19th International Conference on Pattern Recognition*, pp. 1-4, 2008.

[20] V. Struc and N. Pavesic, "The Complete Gabor-Fisher Classifier for Robust Face Recognition", *EURASIP Journal of Advances in Signal Processing*, Vol. 2010, No. 1, pp. 1-16, 2010.

[21] M. Turk and A. Pentland, "Eigenfaces for Recognition", *Journal of Cognitive. Neuroscience*, Vol. 3, No. 1, pp. 71-86, 1991.

[22] P.N. Belhumeur, J.P. Hespanha and D.J. Kriegman, "Eigenfaces vs. Fisherfaces: Recognition using Class Specific Linear Projection", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 19, No. 7, pp. 711-720, 1997.

[23] B. Zeinali, A. Ayatollahi and M. Kakooei, "A Novel Method of Applying Directional Filter Bank (DFB) for Finger-Knuckle-Print (FKP) Recognition", *Proceedings of 22nd Iranian Conference on Electrical Engineering*, pp. 500-504, 2014

[24] W. El Tarhouni, M.K. Shaikh, L. Boubchir and A. Bouridane, "Multi-Scale Shift Local Binary Pattern Based-Descriptor for Finger-Knuckle-Print Recognition", *Proceedings of 26th International Conference on Microelectronics*, pp. 184-187, 2014.

[25] W. Nunsong and K. Woraratpanya, "Modified Differential Box-Counting Method using Weighted Triangle-Box Partition", *Proceedings of 7th International Conference on Information Technology and Electrical Engineering*, pp. 221-226, 2015.