Efficient Biometric Security System Using Intra-Class Finger-Knuckle Pose Variation Assessment

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Abstract--Finger Knuckle Print is a finger based biometric system. It is a model which is the most widespread biometric authentication for an individual. The performance of Finger Knuckle Print recognition algorithms mostly depends on different pose variations. Due to deformations on the finger-knuckle samples, the result of the pose variations leads to false accept rate and it reduces the robustness level. In this paper, an efficient method is introduce to solve the intra-class finger-knuckle pose variations, called the Kernel Intra-Class Finger-Knuckle Pose Density Assessment ('K' Intra-Class FKPDA) to improve the robustness of the biometric system. 'K' Intra-Class FKPDA method map the user's finger-knuckle prints samples in high dimensional feature space using the kernel process. Markov Graphic Model Mapped finger-knuckle print samples on high dimensional feature space to calculate the density level and make out the intra-class pose variations. Bessel Thomson Finger-Knuckle Pose Variation filtering process identified intra-class pose variation and it is removed in 'K' Intra-Class FKPDA method. To reduce the delay time 'K' Intra-Class FKPDA method applies a linear filtering model. Finally, using 'K' Intra-Class FKPDA removed intra-class pose variations and finger-knuckle print is documented with increased robustness level. PolyU FKP Database evaluated Experimental results on 165 images show that the new method can improve the robustness factor appreciably compared with typical Finger Knuckle Print based recognition approaches reducing the filtering delay factor. Experiment is conducted on false acceptance rate, recognition rate, and filtering delay time.

Keywords: Intra-Class Pose Variations, Finger-Knuckle Print, Recognition System, Bessel Thomson Filtering, Markov Graphic Model, High Dimensional Feature Space.

I. INTRODUCTION

The finger-knuckle pose variation quality evaluation is considered to be the most multifaceted issues because simultaneously it concentrates in many factors. In case of finger print, well formed and well structured quality assessment does not exist. As a result, many research peoples have concentrated on the finger-knuckle print recognition.

Finger Knuckle Print Recognition using Phase Congruency (FKPR-PC) induces local features system for finger-knuckle-print recognition [1] was introduced to raise the recognition accuracy using phase congruency. The method affects from deformations on the finger-knuckle samples that are sensitive to pose variations resultant in false accept rate. FKP recognition scheme using Gabor Filter (FKPR-GF) [2] provided biometric authentication by extracting and assembling local and global feature that resulted in a individual authentication system.

In modern time, the topics made attention in the research community are the finger knuckle print. At the same time, as the finger knuckle print is well unique biometric identifier model. Hierarchical Classification (HC) method [4] achieved a good result in terms of robustness, with a predefined threshold value. An Online Finger Knuckle Print (OFKP) [5] was focused to answer the problems related to robustness with the support of Gabor filtering that combined orientation and magnitude information to raise the recognition rate. however accuracy was achieved, but non-elasticity was not proved. Phase-based Local Block (PLB) [6] matching was introduced to increase the recognition rate using phase-based correspondence matching.

One of the most accepted mechanism for human individual authentication is based on hand based biometrics. The advantages of hand based biometrics increased acceptance level. Ant Colony Optimization (ACO) with Fuzzy Binary Decision Tree (FBDT) [7] was applied to execute validation using finger knuckle images. however with the high disorders and pose variations, the validation was inefficient. With the support of capsular pattern [8], high disorders and pose variations were commonly addressed. Discrete Orthonormal ST transform [9] was performed to decrease the error rate whilst verifying the finger knuckle print images by extracting local and global features.

New budding techniques are in the stand using biometric identification. One of the most potential techniques is one of the application of biometric using knuckle images for authentication. Feature based Identification [10] used Gabor filter method to increase the recognition rate. Though, the size of the database was found to be less.

In this paper, we design a Kernel Intra-Class Finger-Knuckle Pose Density Assessment ('K' Intra-Class FKPDA) method to increase the robustness in biometric system. 'K' Intra-Class FKPDA included the following are

1. To solve pose variations and improve the using Kernel Intra-Class Finger-Knuckle Pose Density Assessment ('K' Intra-Class FKPDA).
2. To evaluate the density level by mapping finger-knuckle samples with high dimensional feature space.
3. To reduce the filtering delay time using a linear filtering process.
4. To increase the robustness level by using the kernel process.
5. To remove intra-class pose variation using Bessel Thomson Finger-Knuckle Pose Variation filtering process.

In Section 2 analyzes the improvement of robustness level and reduces the false acceptance rate and provides solutions. Section 3 explains the experimental settings of our proposed method and Section 4 discussed the parametric factors through table and graph. In Section 5, concluding remarks are included.

II. Assessment Method Using Kernel Intra-Class Finger-Knuckle Pose Density

The density assessment in 'K' Intra-Class FKPDA method is a process to identify the finger-knuckle print by removing the pose variations. There are two categories of pose variations namely inter-class finger-knuckle pose variation and intra-class finger-knuckle pose variation. 'K' Intra-Class FKPDA concentrates mainly on removing the intra-class pose variations. The training image is stored in the database and mapping process on test images from the users and authenticated them. Using kernel task the mapping process is carried out in 'K' Intra-Class FKPDA method.

The mapped high dimensional feature space images to compute the density function and identify the pose variations. The sample test images of Finger-Knuckle print density is computed using the Markov Graphic Model and it is also compute the dependency level. Pair wise Morkov is to measure the density level on pair of finger-knuckle print image.

A single user finger-knuckle print with types of pose is analysed. The filtering process is used to avoided intra class pose variations. With a minimal delay time the 'K' Intra-Class FKPDA uses the Bessel Thomson Finger-Knuckle Pose Variation filtering to removal the intra-class variation. The following architecture diagram shows the Kernel Intra-Class Finger-Knuckle Pose Density Assessment ('K' Intra-Class FKPDA) method is illustrated in Figure 3.

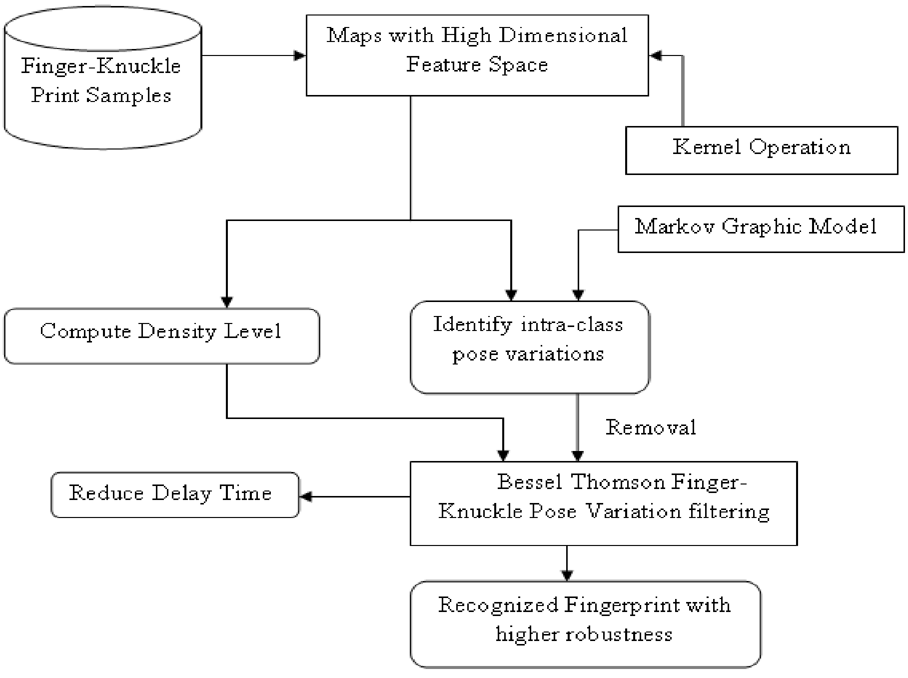

Figure 1 Architecture Diagram of 'K' Intra-Class FKPDA Method

'K' Intra-Class FKPDA Method processing step is clearly illustrated in Fig. 1. The Finger knuckle print samples are mapped using kernel operation with the high dimensional feature space. Within the linear time the kernel task works with the samples and maps with the exact sample space. Using the pair-wise Markov property, the density level is computed and also it identifies the accurate relationship of the training and test finger knuckle samples. Mapping high dimensional feature images using the Markov Graphic model identified by intra-class pose variation. the various low and mid level intra-class pose variations identified by Markov Graphic model.

Algorithmic Procedure of Proposed system

// 'K' Intra-Class FKPDA

Begin

Input: Set of training and test samples are collected

Output: Highly robust finger-knuckle recognition by removing intra-class poses variations

// Kernel Task

Step 1: High Dimensional Feature space Employed

Step 2: Mapping of test and training samples through 'map' function

// Markov Graphic Model

Step 3: Uses Map Function result to identify the density value

Step 3.1: Density value computed using Markov Pair-wise Property

Step 4: If (D=n)

Step 4.1: Achieves robust finger-knuckle recognition

Step 4.2: Goto End

Step 4.3: Else Goto step 5

Step 6: Identifies the intra-class pose variation images

// Bessel Thomson Filtering Process

Step 7: Identified pose variation image filtered

Step 7.1: Compute

Step 7.2: Intra-class Pose variation image filtered out

Step 8: Recognize the finger-knuckle with minimal delay time

End

III. Experimental Evaluation

An effective 'K' Intra-Class FKPDA method made the experimental work on MATLAB coding. The experimental work uses PolyU Finger-Knuckle-Print Database samples. The finger-knuckle-print refers to the intrinsic patterns of the outer surface around the joint of one's finger and serves as an individual biometric identifier. In this research work, finger-knuckle print samples were collected from 165 volunteers. In this samples 125 were male and 40 female's volunteers were in the age group of 20 – 30 years old.

The samples were collected from left index finger, the left middle finger, the right index finger, and the right middle finger. overall, 7920 finger-knuckle images from 660 different fingers were collected with a minimum time of 14 days and maximum time of 96 days using 'K' Intra-Class FKPDA method.

IV. Results Analysis Of 'K' Intra-Class Fkpda Method

The result analysis of 'K' Intra-Class FKPDA method using PolyU Finger-Knuckle Database is compared with Finger Knuckle Print Recognition using Phase Congruency (FKPR-PC). The table 1 shows the False Acceptance rate obtained using MATLAB and comparison is made with FKPR-PC [1] and FKPR-GF [2].

TABLE I. PERFORMANCE OF FALSE ACCEPTANCE RATE USING DIFFERENT METHODS

Finger-Knuckle Print samples	False Finger-Knuckle Acceptance rate (%)		
	'K' Intra-Class FKPDA	*FKPR-PC*	*FKPR-GF*
20	35.43	46.45	54.44
40	39.35	49.37	57.36
60	44.44	56.46	64.45
80	48.52	59.54	67.53
100	42.35	53.37	61.36
120	55.45	66.48	72.47
140	58.35	68.45	75.45

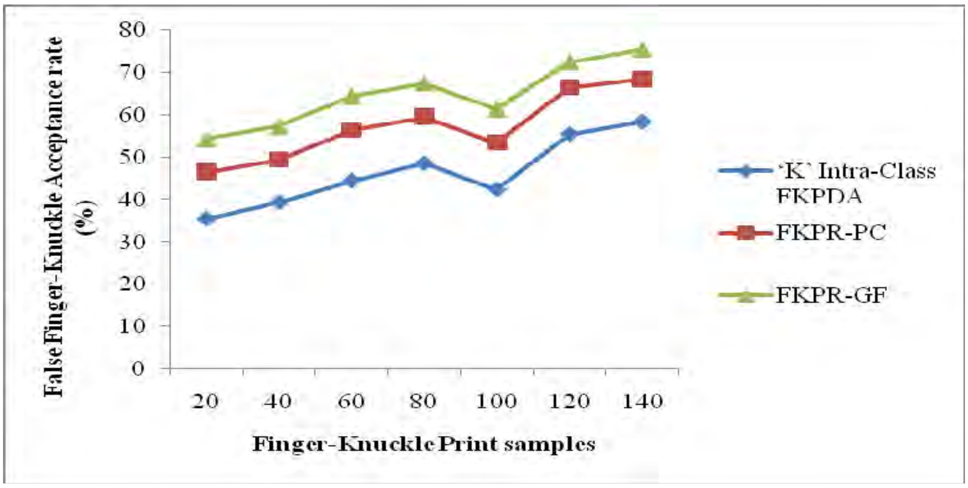

Figure 2 False Acceptance rate curves obtained using various FKPR methods

Fig. 2 describes the False Acceptance rate of finger-Knuckle based on the different FKP samples collected from 100 males and 40 females. Based on the comparision False acceptance rate is proved to be efficient and reduced in the proposed work. This is because of kernel based mapping is achieved by minimizing the false finger-knuckle acceptance rate by 17 – 31 % compared to FKPR-PC [1].

TABLE II. PERFORMANCE OF FINGER KNUCKLE RECOGNITION RATE WITH SAMPLES COLLECTED AT DIFFERENT TIME INTERVALS

Samples collected at time intervals (days)	Finger Knuckle Recognition rate (%)		
	'K' Intra-Class FKPDA	*FKPR-PC*	*FKPR-GF*
2	53.25	43.15	38.15
4	58.75	48.65	40.65
6	65.44	55.34	48.34
8	72.35	62.25	55.25
10	68.55	58.45	51.45
12	75.82	65.72	59.72
14	78.45	68.45	62.45

In table II, Finger Knuckle Recognition rate with respect to the Samples collected at different time intervals. The comparison is made with two more existing systems.

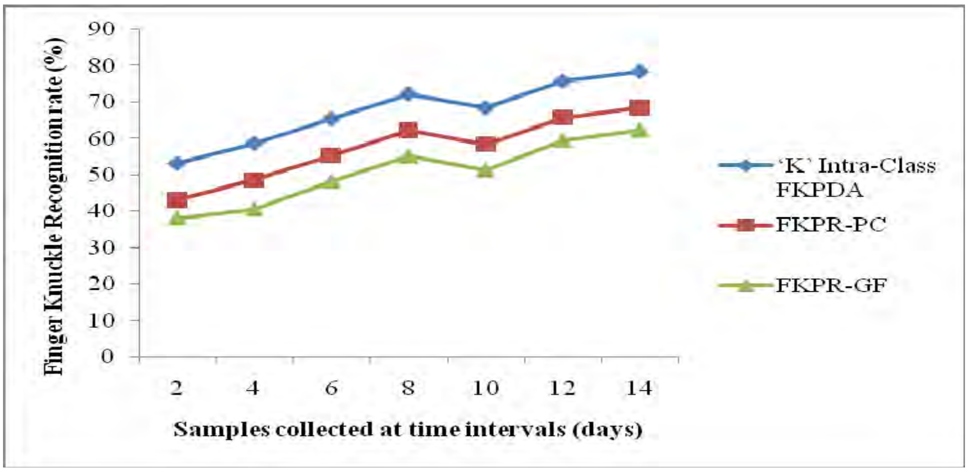

Figure 3 Finger Knuckle Recognition rate curve obtained by 'K' Intra-Class FKPDA, FKPR-PC and FKPR-GF

Performance of the Finger Knuckle Recognition rate over different time intervals, comparison is done with FKPR-PC and FKPR-GF. In Fig. 3, the samples were collected in the time interval of 14 days. Based on the comparision, the Finger Knuckle Recognition rate is improved using the proposed 'K' Intra-Class FKPDA. It is efficient when compared to other existing works. The Markov Graphic model efficiently identifies several low and mid level intra-class pose variations. Using Pair wise Markov property, the presence of intra-class pose variations in the proposed method is successfully identified for further processing and it improves the finger-knuckle recognition rate by 12 – 18 % compared to FKPR-PC [1]. The density level computation separates the density into three modes as shown in figure 6,

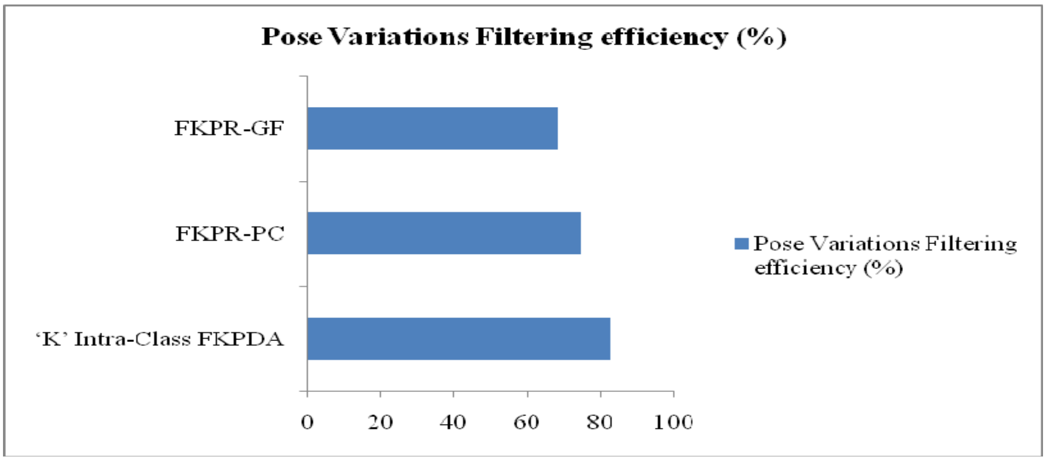

Figure 4 Pose Variations Filtering efficiency curves obtained by three different methods

samples collected in a period of 14 days from 100 males and 40 females are considered for Convergence characteristics of measure of Pose Variations Filtering efficiency with 100 males and 40 females. It is observed that the Bessel Thomson filtering for finger-knuckle print images reach its highest value of 82.35 % in pose variation filtering efficiency compared with other two models which is 74.55 % and 68.35 % respectively. This is because filtering of different pose minimizes the time delay and improves the pose variations filtering efficiency.

Table III. Performance of Filtering Delay Time using different methods

Finger-Knuckle Print samples	**Filtering Delay Time (ms)**		
	'K' Intra-Class FKPDA	***FKPR-PC***	***FKPR-GF***
20	35	47	52
40	38	50	55
60	45	57	62
80	52	64	69
100	43	55	60
120	58	70	75
140	62	74	79

Table III illustrated the results of Filtering Delay Time. It can be seen that increase in the number of finger-knuckle samples achieves lower delay time using ‘K’ Intra-Class FKPDA. But analysis shows that the Filtering Delay Time is lesser than the other two methods.

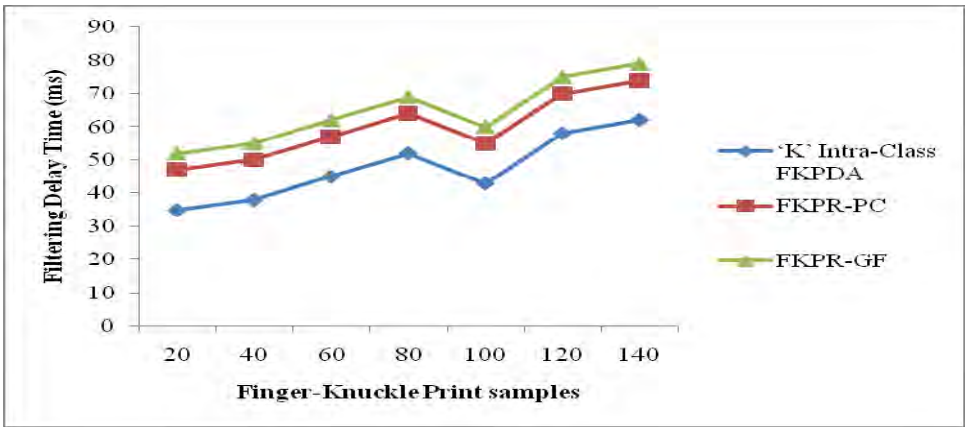

Figure 5. Measure of Filtering Delay Time

In fig. 5, illustrates the Filtering Delay Time from the set of density varying sample images. The filtering delay time is calculated using different 140 samples given as input for experimental purpose and MATLAB simulator applied. Filtering delay time is lower using the proposed ‘K’ Intra-Class FKPDA when compared to existing systems namely, Finger Knuckle Print Recognition using Phase Congruency (FKPR-PC) [1] and FKP recognition scheme using Gabor Filter (FKPR-GF) [2]. Using ‘K’ Intra-Class FKPDA method, the filtering delay time gets reduced by 19 – 34 %. It observes by considering the pose variation image, from the set of density varying samples, the filtering delay time gets reduced by 27 – 48 %.

V. Conclusion

A ‘K’ Intra-Class FKPDA is a design to solve the intra-class finger-knuckle print pose variations and to improve the biometric authentication system robustness. For linear boundary feature of separation based on feature class, adopt kernel operation to map the input finger-knuckle test images from various users with high dimensional feature space. Here markov Graphic Model identified intra-class pose variation level on high dimensional feature space images. Finally, with a minimum time delay to remove the intra-class variation, Bessel Thomson Finger-Knuckle Pose Variation filtering is applied. To improve the efficiency of the biometric system where the finger-knuckle print is recognized with the increased robustness level, ‘K’ Intra-Class FKPDA is applied from the initial to final stage of mapping and recognition stage. Experimental evaluation is conducted with the PolyU to analyze the intra-class pose variation assessment by applying Bessel Thomson filtering. The effectiveness of the proposed method analysis are performed in terms of false finger-knuckle acceptance rate, system recognition rate, and filtering delay time. The ‘K’ Intra-Class FKPDA increases the finger knuckle recognition rate by 30 % and False Finger-Knuckle Acceptance rate is reduced to 53 is efficient when Compared to the existing recognition systems.

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