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A Case Study on Multi-instance Finger Knuckle Print Score and Decision Level Fusions

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ABSTRACT

Abstract—This paper proposed the use of multi-instance as a means to improve the performance of Finger Knuckle Print (FKP) verification. A log-Gabor filter has been used to extract the image local orientation information, and represent the FKP features. Experiments are performed using the DZhang FKP database, which consists of 7,920 images. The influence on biometric performance using Decision and Score Level Fusions has been demonstrated in this paper. Results indicate that the Multi-instance verification approach at Score Level (Max Rule) and Decision Level (OR Rule) outperforms higher performance than using any single instance. Whereas at Score Level (Min Rule) and Decision Level (AND Rule) does not have performance improvement.

Index Terms—: Decision Level Fusion, Multi-Biometric; Multi-instance; Log-Gabor; Score Level Fusion.

1 Introduction

The need for reliable user authentication techniques has increased in the wake of heightened concerns about security and rapid advancements in networking, communication, and mobility. A wide variety of applications require reliable verification schemes to confirm the identity of an individual requesting their service. Examples of such applications include; secure access to buildings, computer systems, laptops, cellular phones, and ATMs. In the absence of robust verification schemes, these systems are vulnerable to the wiles of an impostor [1],[2],[10]. Traditionally, passwords (knowledge-based security) and ID cards (token-based security) have been used to restrict access to applications. However, in these applications security can be easily breached when a password is divulged to an unauthorized user or a badge is stolen by an impostor. The emergence of biometrics has addressed the problems that plague the traditional verification methods.

The term biometric comes from the Greek words bios (life) and metrikos (measure) [10]. Biometric refers to the automatic recognition of individuals based on their physiological and behavioural characteristics. Biometrics systems are commonly classified into two categories: physiological biometrics and behavioral biometrics. Physiological biometrics (fingerprint, iris, retina, hand geometry, face, etc) use measurements from the human body. Behavioural biometrics (signature, keystrokes, voice, etc) use dynamics measurements based on human actions [1],[3].

These systems are based on pattern recognition methodology, which follows the acquisition of the biometric data by building a biometric feature set, and comparing versus a pre-stored template pattern. These are unimodal which rely on the evidence of a single source of information for authentication, which have to contend with a variety of problems such as (noise in sensed data, intra-class variations, and inter-class similarities, etc).

Possible solutions to compensate for the false classification problem due to intra-class variability and inter-class similarity can be found in the fusion of biometric systems or experts [8]. Fusion based on multi-biometrics can also be used to improve performance in a practical system. The fusions of biometric refer as multibiometrics. The term multibiometrics denotes the fusion of different types of information (e.g., fingerprint and face of the same person, or fingerprints from two different fingers of a person). Thus this paper evaluates the performance of multi-instance approach by fusing the data at match score and decision levels using different rules. The rest of the paper is organized as follows: Section 2 presents related works, proposed method is given in section 3, experimental results are given in Section 4, and conclusion is mentioned in Section 5.

2 Related Work

Lin Zhang et al.[4] proposed an effective FKP recognition scheme by extracting and assembling local and global features of FKP images. Specifically, the orientation information extracted by the Gabor filters is coded as the local feature. The proposed scheme exploits both local and global information for the FKP verification. The authors experimental results conducted on FKP database indicate that the proposed scheme could achieve much better performance in terms of EER and the decidability index than the other state-of- the-art competitors.

T.C. Faltemier et al. [6] proposed a multi-instance enrollment for face recognition as a means to improve the performance of 3D face recognition. The authors show that using

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multiple images to enroll a person in a gallery can improve the overall performance of a biometric system. The authors demonstrated that when using multiple images to enroll a person, sampling from different expressions improves performance over sampling only the same expression.

M. Vatsa, et al. [7] proposed a generalized biometric match score fusion framework using belief function theory. Multi-instance iris verification and multi-unit iris verification are used as the two case. Experimental results show that the proposed fusion framework with PCR rule can effectively fuse the match scores even when the individual biometric classifiers provide highly conflicting match scores

Tobias Scheidat, et al. [8] proposed a fusion of two instances of the same semantic, where semantics are alternative handwritten contents such as numbers or sentences, in addition to commonly used signature. The fusion is carried out by the combination of the matching scores of two instances of one handwritten semantic. The authors demonstrated that when using three semantics and fusion strategies, improvements can be observed in comparison to the best individual results.

3 Multibiometrics Fusion

3.1 Fusion Strategies

The term multibiometrics denotes the fusion of different types of information. Multibiometric systems can offer substantial improvement in the matching accuracy of a biometric system depending upon the information being combined and the fusion methodology adopted [1]. **Multi-sensor**: Multiple sensors can be used to collect the same biometric. **Multi-modal**: Multiple biometric modalities can be collected from the same individual, e.g. fingerprint and face, which requires different sensors. **Multi-sample**: Multiple readings of the same biometric are collected during the enrolment and/or recognition phases, e.g. a number of fingerprint readings are taken from the same finger. **Multi-algorithms**: Multiple algorithms for feature extraction and matching are used on the same biometric trait.

Multi-instance: Multi-instance biometrics means the use of the same type of raw biometric sample and processing on multiple instances of similar body parts, (such as two fingers, or two irises) also been referred to as multi-unit systems in the literature [9]. These systems can be cost-effective since a single sensor is used to acquire the multi-unit data in a sequential fashion, and these systems generally do not necessitate the introduction of new sensors nor do they entail the development of new feature extraction and matching algorithms. Multi-instance systems are especially beneficial to users whose biometric traits cannot be reliably captured due to inherent problems. Multi-instance systems are often necessary in applications where the size of the system database (i.e., the number of enrolled individuals) is very large (FBI's database currently has 50 million ten-print images, and multiple fingers provide additional discriminatory information) [9]. Combination of multi-instances can improve the performance of the biometric system.

3.2 Levels of Fusion

Based on the structure of a biometric authentication, there are four levels within the process to fuse biometric systems, they are [11],[12]: **Sensor Level Fusion;** entails the consolidation of evidence presented by multiple sources of raw data before they are subjected to feature extraction. Sensor level fusion can benefit multi-sample systems which capture multiple snapshots of the same biometric. **Feature Level Fusion**; consolidating the feature sets obtained from multiple biometric algorithms into a single feature set (vector), after normalization, transformation and reduction schemes.

Score Level Fusion; fusion at the matching score level is the most popular fusion strategy in the field of multi-biometrics. The performance of this fusion strategy can be seen in numerous studies. Along with different biometric traits can be fused at the matching score level; matching score level fusion may be also performed for two distinct kinds of features generated from the same biometric trait [9]. The matching score level fusion, considers the matching score outputs of the individual biometric traits as a feature vector and then personal authentication is performed on the basis of this feature vector.

Decision Level Fusion; falls under a broader area known as distributed detection systems and is the process of selecting one hypothesis from multiple *M* hypotheses given the decisions of multiple *N* sensors in the presence of noise and interference. In biometrics, decision level fusion creates a single decision from typically two hypotheses, imposter or genuine user, from multiple biometric sensor decisions, which may or may not be identical sensors. Often, decision level fusion is implemented to save communication bandwidth as well as improve decision accuracy. A statistical performance model for each biometric sensor is needed a prior to support the system wide optimization in terms of two error rates: false acceptance rate (FAR), admitting an imposter, and false rejection rate (FRR), rejecting the genuine user.

In all the experiment, the data have been fused at score and decision level fusions using different rules (decision "OR and AND" rules, score "Max and Min" rules) for two and three instances combination out of four fingers.

4 Proposed Method

4.1 Choice of the Modality

In this paper a hand-based biometric technique, finger-knuckle-print (FKP) have been used, FKP refers to the image pattern of the outer surface around the phalangeal joint of one's finger, which is formed by bending slightly the finger knuckle [4]. The experiments are developed for personal authentication using DZhang FKP data base. FKP images were collected from 165 volunteers, including 125 males and 40 females. The database contains FKPs from four different fingers, right index, right middle, left index, and left middle fingers. The DZhang database is available at the website of Biometrics Research Centre, the Hong Kong Polytechnic University.

4.2 Pre-Processing

This section describe the Region of Interest (ROI) extraction, the process involved to extract ROI for each instance is as follows. It is necessary and critical to align FKP images by adaptively constructing a local coordinate system for each image. With such a coordinate system, ROI can be cropped from the

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original image using the steps suggested in [4], as shown in Fig-1.

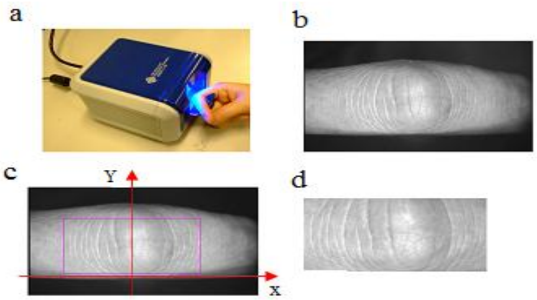

Fig-1: **a**)Image acquisition device is being used to collect FKP samples **b**)Sample FKP image **c**)ROI coordinate system, where the rectangle indicates the ROI area **d**)Extracted ROI

4.3 Feature Extaction

Log-Gabor has been used as feature extraction algorithm; it eliminates the limitations in Gabor filters. Log-Gabor functions, by definition, always have no DC component, and, the transfer function of the log Gabor function has an extended tail at the high frequency end. Log-Gabor function proposed by Field [5], Field suggests that natural images are better coded by filters that have Gaussian transfer functions when viewed on the logarithmic frequency scale. On the linear frequency scale log-Gabor has a transform function of the form

$$G(w) = e^{(-\log(w/w_0)^2)/(2(\log(k/w_0)^2)}$$

where w_0 is the filter's centre frequency. To obtain constant shape ratio filters the term k/w_0 must be held constant for varying w_0.

5 Result and Discussion

This section deals with the investigation consequences comparison of combining many biometrics at score and decision level fusion to measure the performance of multi-instance system. In all the experiments, performance is measured in terms of False Acceptance Rate (FAR in %) and corresponding Genuine Acceptance Rate (GAR in %). First the performance of a single instance biometric system is measured; later the results for multi-instance biometric system are evaluated. The results obtained from single instance biometric system are tabulated in Table-1, and depicted as Receiver Operating Characteristic (ROC) curve in Figure-2.

TABLE 1
Single Instance Performance

FAR (%)	GAR (%)			
	Right-Index (RI)	Right-Middle (RM)	Left-Index (LI)	Left-Middle (LM)
0.01	72.00	75.00	63.00	70.00
0.10	78.00	82.33	71.67	76.67
1.00	86.33	89.67	86.33	86.33

From Table-1 it can be observed that the right middle finger has more score performance than the other fingers.

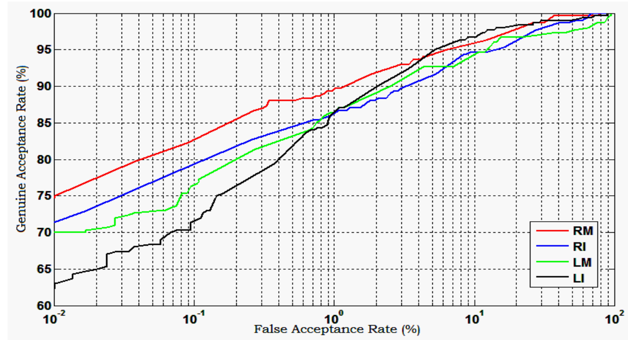

Fig-2: The ROC Curve Performance of Single Instance.

Go further the experimental results of the fusion of two and three instances, under Decision and Score Level Fusions, are shown. Table-2 shows the fusion result of two instances and Table-3 shows the fusion result of three instances.

TABLE 2
The Fusion Result Of Two Instances

FAR (%)	GAR (%) Decision Level (OR Rule)					
	RI+RM	RI+LI	RI+LM	RM+LI	RM+LM	LI+LM
0.01	88.67	72.00	76.67	77.67	81.67	81.00
0.10	91.00	80.00	85.33	85.33	87.00	86.00
1.00	94.67	95.00	94.00	93.67	95.00	94.00
	GAR (%) Decision Level (AND Rule)					
0.01	72.33	66.00	67.00	67.67	67.67	64.00
0.10	79.67	78.00	78.00	78.33	76.67	74.33
1.00	86.00	86.67	85.67	88.33	86.67	85.33
	GAR (%) Score Level (Max Rule)					
0.01	86.33	72.00	76.67	77.67	81.67	81.00
0.10	91.00	81.33	85.00	85.33	87.00	86.33
1.00	94.67	95.00	94.00	94.67	95.00	94.00
	GAR (%) Score Level (Min Rule)					
0.01	72.33	66.00	67.00	73.67	67.67	64.67
0.10	79.67	78.67	78.33	78.33	76.67	74.67
1.00	86.00	86.67	85.67	90.33	86.67	85.33

From Table-2 it can be observed that the fusion of two instances finger at score level (Max rule) and decision level (OR rule) has a significant improve score over the single instance. Whereas at score level (Min rule) decision level (AND rule) does not have performance improvement over a single instance, since both matchers has to agree for the decision to be true (in case of AND). For this reason the performance will be like the best matcher. Fig-3 shows the ROC curve for the performance fusion of two instances.

From Table-3 it can be observed that the fusion of three instances at score level (Max rule) and decision level (OR rule) has more improvement over the fusion of two instances, with some better performance of level (Max rule) over decision level (OR rule). Whereas at score level (Min rule) and at decision level (AND rule) does not have performance improvement even over a single instance for the same reason shown above. Fig-4 shows the ROC curve for the performance of the fusion of three instances.

TABLE 3
THE FUSION RESULT OF THREE INSTANCES

FAR (%)	GAR (%)Decision Level (OR Rule)			
	RI+RM+LI	RI+RM+LM	RI+LI+LM	RM+LI+LM
0.01	83.33	86.00	84.33	87.67
0.10	89.67	91.00	90.00	92.33
1.00	98.00	97.00	96.33	97.00
	GAR (%) Decision Level (AND Rule)			
0.01	71.00	68.00	65.33	65.33
0.10	80.67	77.67	74.67	73.00
1.00	88.00	86.00	86.00	88.00
	GAR (%)Score Level (Max Rule)			
0.01	83.33	86.00	87.00	88.67
0.10	90.00	91.00	93.00	93.00
1.00	98.00	97.00	99.33	99.00
	GAR (%)Score Level (Min Rule)			
0.01	54.00	74.00	60.67	60.67
0.10	74.67	78.00	74.67	73.00
1.00	84.67	85.67	84.33	85.67

6 CONCLUSION

Analyzing the performance of using FKP images as a biometric has been done. From the analysis of experimental results and observations it can be concluded that a multi-instance biometric fusion is given better performance at score level (Max rule) and decision level (OR rule) than single instance. Whereas at score level (Min rule) and at decision level (AND rule) does not have performance improvement. This shows that using multiple instance of biometric which collected using single sensor; can have the security level. However, from the experimental results and observations the degree of improvement in accuracy by fusing multiple instances is marginal. Since different instance of the same trait produces the same redundant features.

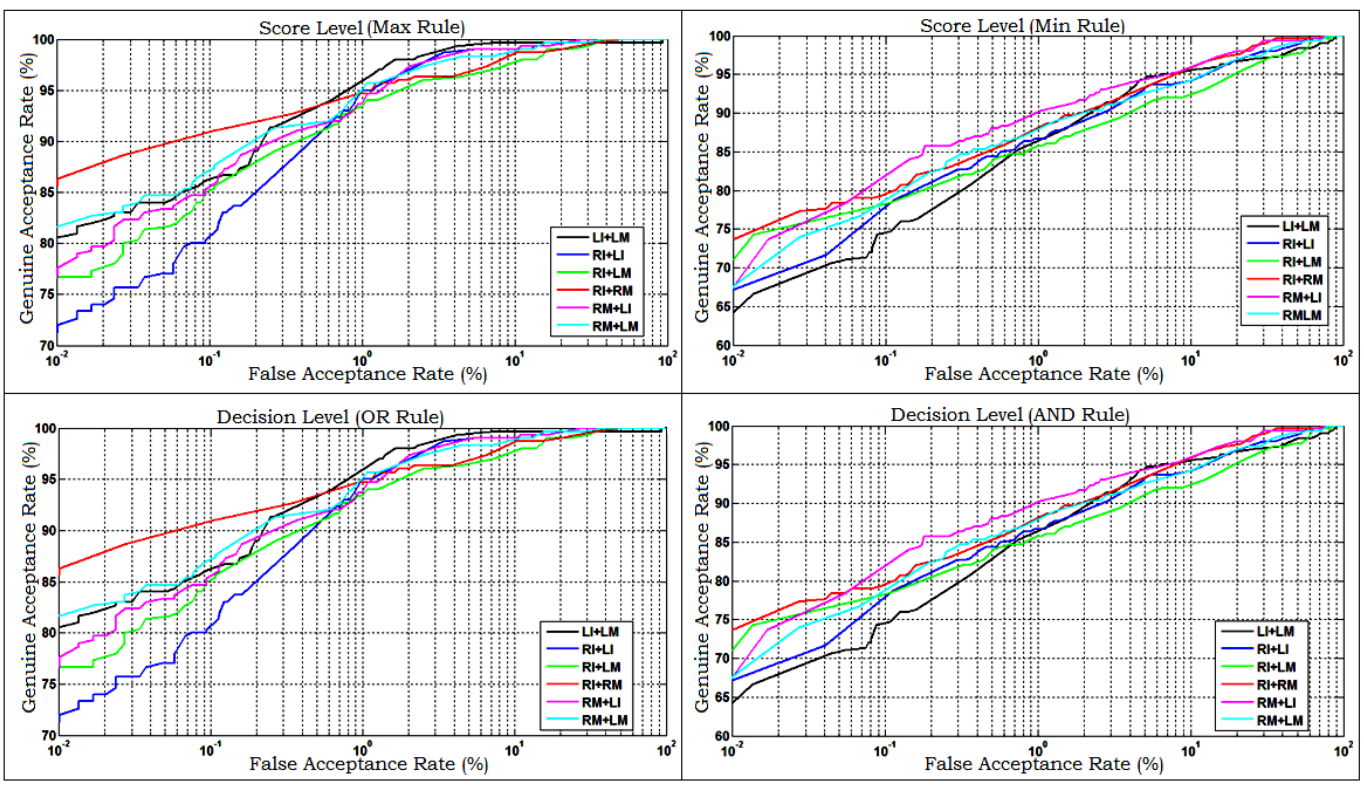

Fig-3 The ROC curve Performance at Score and Decision Level Fusions combination of two Instances **a**) Score Level (Max Rule) **b**) Score Level (Min Rule) **c**) Decision Level (OR Rule) **d**) Decision Level (AND Rule).

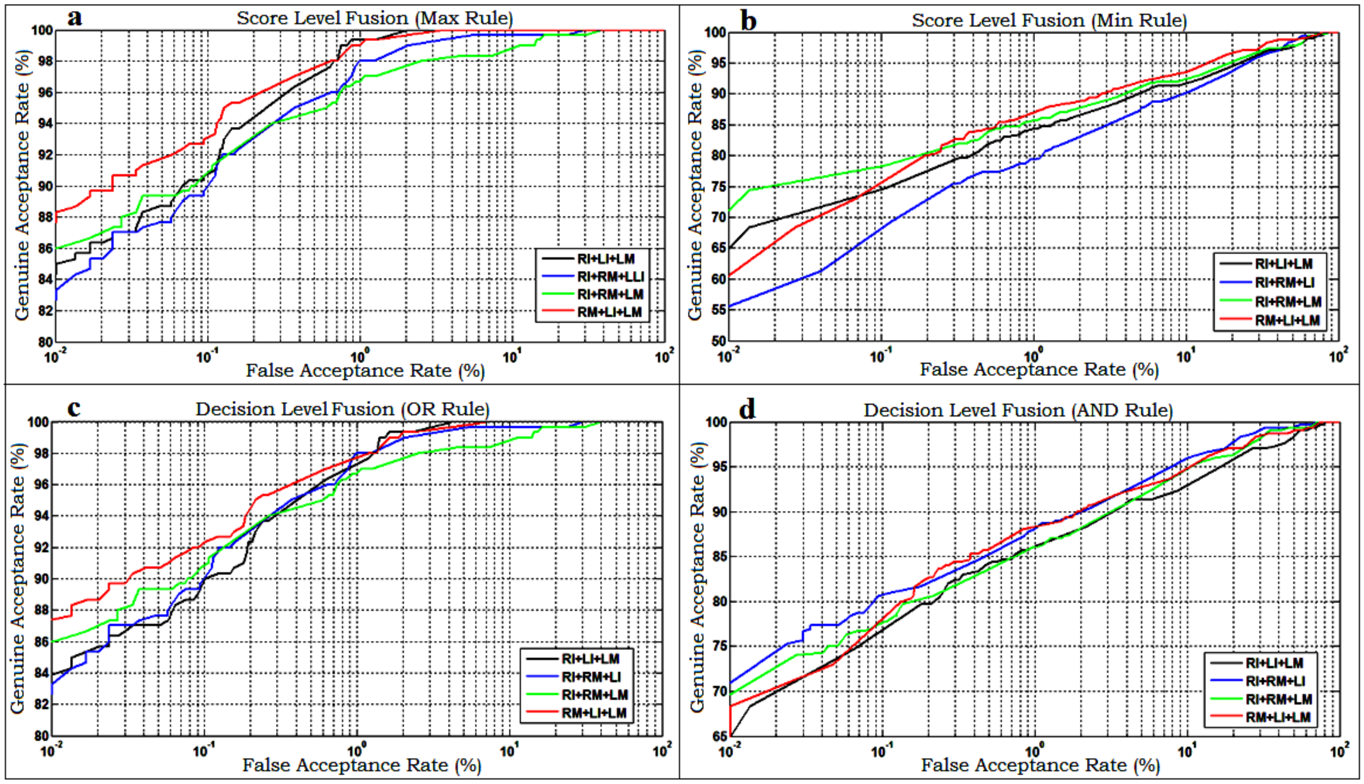

Fig-4: The ROC curve Performance at Score and Decision Level Fusions combination of three Instances **a**) Score Level (Max Rule) **b**) Score Level (Min Rule) **c**) Decision Level (OR Rule) **d**) Decision Level (AND Rule).

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