Biometric Authentication Methods Based on Ear and Finger Knuckle Images

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Abstract

Multimodal biometric methods use different fusion techniques to avoid authentication problems such as noisy sensors data, non-universality, and unacceptable error rates. Fusion methods have been proposed in different levels such as feature level and classification level. In this paper, we propose two multimodal biometric authentication methods using ear and finger knuckle (FK) images. A method based on fusion of images of ear and FK before the feature level is proposed, thus there is no information lost. A multi-level fusion method at image and classification levels is also proposed. The features are extracted from the fused images using different classifiers and then combine the outputs of the classifiers in the abstract, rank, and score levels of fusion. Experimental results show that the proposed authentication methods increase the recognition rate compared to the state-of-the-art methods.

Keywords: *Biometric Data, Authentication Methods, Ear and Finger Knuckle Images, Image Fusion*

1. Introduction

Biometric systems use behavioral or/and physiological traits such as face, ear, iris, fingerprints, and palm-print of individuals for authentication. Biometrics that use one trait for identifying persons (unimodal biometric systems) face problems of noisy sensors data, non-universality, unacceptable error rates, and spoof attacks. Multimodal biometric authentication techniques attract much attention of many researches recently as the fusion between many different modalities can increase the recognition rate. The fusion can be achieved in different levels such as sensor, feature, or classification level. The literature reported that the multimodal biometric methods achieve better recognition rates than unimodal biometric methods.

From the unimodal biometrics data, two traits of ear and finger knuckle are recently used for authentication [1-8, 20-21]. Chang et al. [1] compared ear and face recognition rates using a principal component analysis (PCA) technique on faces and ear images. In a multimodal experiment for combining ear and face images, the recognition rate was 90.9%. Zhang et al. [2] combined the left and right ears to increase the recognition rate. They achieved recognition rate of 93.3% by using one ear image (left or right) and 95.1% by combining left and right ear images. Theoharis et al. [3] combined 3D face and 2D ear biometrics. They reported recognition rate of 99.7% by combining face and ear images. Feature combination is used in [4] to improve the recognition rate of ear recognition system. Ravikanth et al. [5, 6] used linear subspace methods to extract finger knuckle (FK)'s features. They combined the output of three classifiers at score level using sum, product, and product of sum rules. Zhang et al. [7] combined two FKs and achieved recognition rate ranging from 99.28% to 99.69%. In another experiment, they combined four FKs and used sum and minimum rules[8].

This paper proposes two authentication methods using ear and FK images to increase the recognition rate. We propose a method based on an image-level fusion. The fusion of images of ear and FK is done before the feature level, thus there is no information lost. We also propose a multi-level fusion method at the image-level and the classification-level. The features are extracted from the fused images using different classifiers and then combine the outputs of these classifiers in the abstract, rank, and score levels of fusion. Experimental results show that the proposed authentication methods increase the recognition rate compared to the state-of-the-art methods.

2. Conventional Algorithms

2.1 Biometric Data

Biometric systems use different physiological traits such as face, iris, fingerprints, ear, finger knuckle, and palm-print of individuals for recognition purposes. Biometrics that use one trait for authentication face problems of noisy sensors data, non-universality, and unacceptable error rates. Thus, multimodal biometric systems is needed to solve these problems.

In this paper, we used two recent unimodal biometrics of ear and finger knuckle. The size of ear images are small thus it needs small computational time. In addition, the ear images does not affect by expressions, mode, or health and need not to contact with sensors. On the other hand, FK image has many features than other biometrics. However, these data may face the problem of pose, illumination, or occlusion. Combining ear and FK images is able to solve these problems and increase the recognition rate.

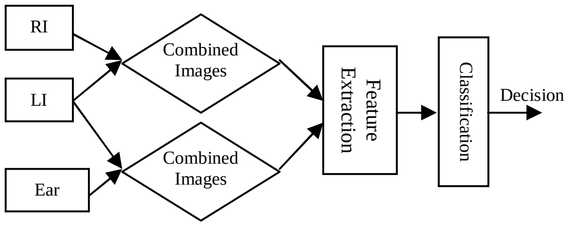
2.2 Authentication Algorithms

Sensor Level Fusion, In sensor level fusion, various systems are used to sample the same biometric such as multi-instances and multi-sensorial systems. Multi-instances system uses many sensors to capture samples of more different instances of the same biometric (e.g. Multi fingers, left and right ears). While, multi-sensorial systems samples the same instance of a biometric with two or more different sensors (e.g. both visible light and infrared camera) [9].

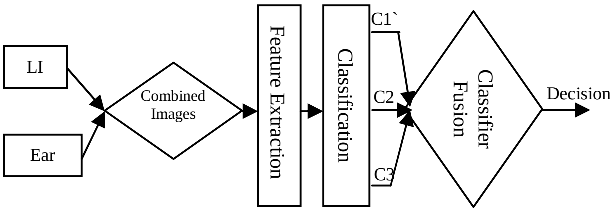
Feature Level Fusion, The combination of features in this level can achieve good results because it has more information than in the classification level. The fusion of features is usually implemented by concatenating two or more low dimensional features to form a long vector. Assume f1 = {x1, ..., xn}, f2 = {y1, ...,ym} are two feature vectors with two different sizes n, m respectively. f={ x1,..., xn,...., y1,....,ym}, can represent the concatenation of the two feature vectors f1 and f2.

Classification Level Fusion, Combining classifiers technique achieves good recognition rates when the classifiers used are independent. The fusion in this level may be in the abstract, rank, or score levels. Abstract (decision) level fusion makes a decision by combining the outputs of different classifiers for a test image. Many researches focus on producing a pool of classifiers and select the most diverse and accurate classifiers. The most diverse ensemble, Giacinto and Roli [10], uses the double fault measure (DF) [11] and the Q statistics [12] form a pairwise diversity matrix for a classifier pool and subsequently to select classifiers that are least related. Other abstract level fusion methods are clustering and selection [13], and thinning the ensemble [14].

Rank level fusion sorts the output of each classifier (a subset of possible matches) in decreasing order of confidence so that each class has its own rank. The fusion can be done through counting the ranks of each class and decision will be class of highest rank. Score (measurement) level fusion applies fusion rules on the vectors that represents the distance between the test image and the training images; the output of each classifier and the decision is the class that has the minimum value. Assume that, the problem of classifying an input pattern Z into one of m possible classes based on the evidence provided by R



(a) Image Level Fusion Method



(b) Multi-Level Fusion Method

Figure 1. Block diagram of the proposed fusion methods

different classifiers. Let $\vec{x}_i$ be the feature vector (derived from the input pattern Z) presented to the ith classifier. Let the outputs of the individual classifiers be P(ωj|$\vec{x}_i$), i.e., the posterior probability of the pattern Z belonging to class ωj given the feature vector $\vec{x}_i$. Let c $\in${1, 2, ..., m} be the class to which the input pattern Z is finally assigned. The following rules is used to determine the class c [9]: c= arg maxj maxi P(ωj|$\vec{x}_i$), c= arg maxj mini P(ωj|$\vec{x}_i$), c= arg maxj medi P(ωj| $\vec{x}_i$), c= arg maxj avgi P(ωj| $\vec{x}_i$), and c= arg maxj Πi P(ωj| $\vec{x}_i$).

3. Proposed Methods

In the sensor level, the data obtained from different sensors may not be compatible, such as a data collected from cameras with different resolutions. In the feature level fusion, a long feature vector can become high dimensional if many unimodal biometrics are added. In addition, the combination in classifier-level can achieve good results only if the combined classifiers are independent or diverse. In all cases, many data can be lost.

3.1 Image-Level Fusion Algorithm

The goal of image fusion is to integrate multimodal, multiview, multisensor, multifocus, and multitemporal [15] information into a new image containing information of which quality could not be achieved otherwise. A wide range of application areas utilizes image fusion. The fused image is suitable for the purposes of human/machine perception, and image processing tasks.

This paper uses images of ear and FKs, which are collected from different sensors, and concatenate them side by side to get one image. The combined image then has all the features of ear and FKc images together. Figure 1 shows the block diagram of the proposed fusion methods. We combine two images of FK (Left Index (LI) and Right Index (RI)) and also combine ear and FK (LI) images before the feature level as shown in Figure 1.a. The feature extraction and classification are done for the combined images.

3.2 Multi-Level Fusion Algorithm

We also propose a multi-level fusion algorithm at image level and classification level. First, we combine ear and FK (LI) images and extract the features of the combined image as shown in Figure 1.b. Then, we classify these features using many classifiers (C1, C2, and C3) and combine the output of these classifiers in the abstract, rank, and score levels fusion (multi-level fusion). The outputs of nearest neighbor classifiers using majority voting is used in the abstract level, while the Borda count fusion method is used in the rank level.

4. Experiments

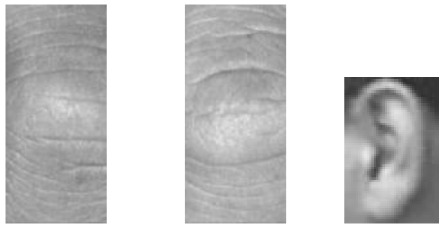
4.1 Experimental Setup

In order to evaluate the proposed multimodal biometric methods, two different types of image databases for ear and FK are used. The FK images database [16] were collected from 165 volunteers, including 125 males and 40 females. Ear images database [17], consists of gray scale images in PGM format. We used six ear and FK images in our experiments. One images (1 ear image and 1 FK image) have been used for the training phase and the rest of the images are used for the testing phase. Figure 2 shows samples of FK images (Left Index (LI) and Right Index (RI)) and also an ear image.

Linear Discriminant Analysis (LDA), Discrete Cosine Transform (DCT), and Discrete Wavelet Transform (DWT) are used as feature extraction methods. Minimum distance (Euclidean, City Block, and Cosine), Radial Basis Function (RBF), and Probabilistic Neural Network (PNN) classifiers are used in the evaluation.

4.2 Results

In the experiments, first the ear and FK unimodal biometric method with no fusion is evaluated as shown in



(a) (b) (c)

Figure 2. Samples of the FK and ear images, (a) Left Index (LI), (b) Right Index (LI), (c) Ear.

Table 1. We then apply the fusion on ear and FK models separately in the classification level as shown in Table 2. Next, we implement the feature level fusion to combine the features of ear and FK and combine the features of two different FKs. The results are shown in Table 3. The fusion in classification level (score, rank, or abstract) achieved recognition rate better than using single classifier as shown in Tables 1 and 2. The fusion in score level is superior than rank or abstract levels because it has more information.

Median and product rules achieved the best results in score level fusion and thinning ensemble method achieved the best results in abstract level fusion. The recognition rate in features level using ear or FK models is approximately equal to the results with no fusion as shown in Table 3.

The recognition rates of the proposed methods are shown in Tables 4 and 5. Table 4 shows the results of the combined images of ear and FK and two different FKs before extracting features as proposed in Figure 1(a). The results show that the fusion of images achieved better recognition rate than the fusion in match or feature levels because there is no information lost. However, combining ear and FK reported rates better than combining two fingers FK, because ear and FK are more independent. Table 5 shows the results of combining ear and FK images and then applying the fusion in classification level as proposed in Figure 1(b). Results show that the combination in early stages achieves the best recognition rates.

Recognition Rates of the state-of-the-art methods for ear and FK are shown in Table 6. In this table, [8], combined two or four FKs in score level, [18] combined two FKs in abstract level, [2] combined left and right ears, [4] achieved high recognition rate when they combined ear features, and [19] used feature fusion approach. Results show that the proposed multi-level fusion method increases the recognition rate in comparison to the state-of-the-art methods.

Table 1. Recognition Rate (%) for Ear and FK with no fusion

		LDA	DCT	DWT
Ear	Euclidean	92.94	88.24	88.24
	City Block	90.59	85.88	88.24
	Cosine	84.71	83.53	83.53
	PNN	92.94	88.24	88.24
	RBF	84.71	77.41	78.41
FK	Euclidean	84.71	84.71	84.71
	City Block	85.88	96.47	85.88
	Cosine	82.35	75.29	75.29
	PNN	84.71	84.71	84.71
	RBF	75.77	77.06	77.06

Table 2. Recognition rate (%) for the fusion in the classification level

			LDA	DCT	DWT
Ear	Score Level	Min	84.71	83.53	84.71
		Max	90.59	85.88	88.24
		Product	89.41	85.88	89.41
		Mean	90.59	85.88	88.24
		Median	92.94	88.24	89.41
	Rank Level	Borda Count	92.94	88.24	88.24
	Abstract Level	Whole Ensemble	92.94	87.06	82.35
		Most Diverse	91.77	84.71	87.06
		Thinning Ensemble	92.94	88.24	88.24
		Clustering	92.94	83.53	83.53
FK	Score Level	Min	82.35	75.29	75.29
		Max	85.88	83.53	85.88
		Product	84.71	87.06	87.06
		Mean	85.88	82.35	85.88
		Median	84.71	84.71	84.71
	Rank Level	Borda Count	85.88	85.88	85.88
	Abstract Level	Whole Ensemble	83.53	83.53	84.71
		Most Diverse	40	81.18	74.12
		Thinning Ensemble	87.06	84.71	84.71
		Clustering	84.71	84.71	84.71

Table 3. Recognition rate (%) for the fusion in the feature level

			LDA	DCT	DWT
Ear+FK	Feature Fusion	Euclidean	98.82	91.77	96.47
		CityBlock	97.65	94.12	95.29
		Cosine	96.47	88.24	85.88
LI+RI	Feature Fusion	Euclidean	94.12	89.41	97.65
		City Block	92.94	91.77	94.12
		Cosine	78.83	84.71	83.53

Table 4. Recognition rate (%) for the proposed image level fusion method shown in Figure 1(a)

			LDA	DCT	DWT
Ear+FK	Combine Images	Euclidean	98.82	96.47	96.47
		CityBlock	98.82	100	96.47
		Cosine	96.47	84.71	84.71
LI+RI	Combine Images	Euclidean	94.12	97.65	97.65
		City Block	92.94	98.82	94.12
		Cosine	78.82	83.53	83.53

Table 5. Recognition rate (%) for the proposed multi-level fusion method shown in Figure 1(b)

			LDA	DCT	DWT
Ear+FK(Combine Images)	Score Level	Min	96.47	84.71	84.71
		Max	98.82	100	96.47
		Product	98.82	97.65	97.65
		Mean	100	100	96.47
		Median	98.82	96.47	96.47
	Rank Level	Borda Count	100	97.65	97.65
	Abstract Level	Whole Ensemble	98.82	96.47	96.47
		Most Diverse	100	89.41	89.41
		Thinning Ensemble	98.82	96.47	96.47
		Clustering	98.82	96.47	96.47

Table 6. Recognition Rate of the state-of-the-art methods for Ear and FK

FK	Zhang et al.[8] Single finger Two fingers Four fingers	98.22% - 98.56% 99.73% - 99.8% 100%
	A. Kumar et al. [18]	94.5% - 98.64%
Ear	Lu et al. [2]	95.1%
	Alaa et al. [4]	94.12% - 96.1 %
	Arbab et al. [19]	97.4%

5. Conclusions

In this paper, we proposed two multimodal biometric authentication methods using ear and FK images. We proposed method based on an image-level fusion and multi-level fusion method at the image-level and the classification-level. Experiments show that the fusion in early stages increases the recognition rate and combining ear and FK is better than combining two different FKs. Score level reported better results than rank or abstract levels and the multi-level fusion achieved the best results. As a future work, we intend to apply more fusion methods for other biometrics.

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