

An Efficient Multimodal Biometric Authentication Integrating Fingerprint and Face Features

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Abstract: Biometrics authentication has been used in many applications such as e-commerce, access control etc. In this research, multimodal biometric authentication in light of score level combination of fingerprint and face is proposed. Face and fingerprint is two of the most popular biometric traits and can complement each other for more reliable user authentication. To verify the effectiveness of the proposed method, FERET, SDUMLA-HMT and FVC2002 databases are used in this research. Furthermore, experimental results showed that the proposed fusion based method for fingerprint and face recognition can improve the performance in terms of Equal Error Rate (EER). Eventually, the experimental result shows that our proposed fusion based technique appears to be promising with 7.01~9.13% of EER based on the different datasets.

Keywords: Biometrics, Multimodal, Fingerprint, Face, Features, Fusion

Introduction

In this era, there are various situations that people need to authenticate themselves. Authentication is a process to determine that someone is really the person that he claimed to be or not. Generally, there are three types of authentication which are something you know, something you have and something you are. Password is an example for something you know. Password is the most common technique used by people to authenticate themselves. However, password needs a complex combination to make it secure and it is not easy to remember a complex combination. In addition, the example of something you have is token. Token will generate a random number then people need to input that random number into the system. Next, a system will verify that random number. However, it is not convenient to carry token anywhere as it might be lost or stolen. The last authentication type is something you are. People can authenticate themselves without remembering the complex combination or carry any devices. People only need their own traits to authenticate themselves, for example, their eyes, retina, hand, fingerprint, etc. This authentication method is called biometrics. Biometrics uses physiological or behavioural human traits for authentication purposes. The physiological traits include face, fingerprint, palm, retina and etc and the behavioral traits include gait, speech, signature and etc. Based on

the number of traits, biometrics can be categorized as unimodal and multimodal. Unimodal biometrics is a biometric system that use single trait for authentication. This type of biometrics has some limitations such as noisy sensor data, spoof attack, non-universality and unacceptable error rate.

On the other hand, multimodal biometrics is a biometric system that use more than one characteristic of recognition. Multimodal biometrics can overcome limitation of unimodal biometrics because it has multiple information from different sources (Sarhan *et al.*, 2016). Furthermore, multimodal biometrics has some advantages like more robust to noise, improve the accuracy, more secure and can solve the non-universality problem.

Thus, the development of multimodal biometric is fast and there are many kinds of combinations of biometrics, such as fingerprint and finger vein, face and iris, face and gait, iris and retina.

In this study, multimodal biometric authentication that based on face and fingerprint is proposed. The fusion between face and fingerprint is proposed because both of them are the most popular biometric traits and the device for capturing face and fingerprint images is affordable.

Fusion Levels of Multimodal Biometrics

In multimodal biometrics, there are various level of fusion possibility, such as:

- Data level: Fused the original biometrics data, for example: Combining face and fingerprint image
- Feature level: Combining the extracted biometric features with another biometric features
- Score level: Matching score of different biometric systems are fused together and produce a single score
- Decision level: Combining the decision that has been made from each of biometric system

Each of fusion level has its own strengths and weaknesses. Table 1 shows some advantages and disadvantages of each of fusion level.

It is believed that fusion on the earlier level is better. Feature level fusion is expected to provide a better result compare with score level or decision level because feature contains more information. Notwithstanding, the combination at feature level is troublesome in light of the fact that list of the feature set of various modalities is not compatible with each other. Thus, fusion in score level is better because it is not hard to get and fusion the matching score from different modalities (Ross and Jain, 2003; 2004).

Proposed Method for Fingerprint and Face Recognition

Fingerprint Recognition

In this study, the minutiae-based technique is chosen for fingerprint recognition because of its simplicity and robustness. There are four main processes in fingerprint recognition: Pre-processing, minutiae extraction, post processing and matching.

Pre-Processing

Pre-processing is an important step in fingerprint recognition. By implementing a good pre-processing technique, the minutiae can be extracted easily. In this step, fingerprint images are enhanced using Short Time Fourier Transform (STFT) (Chikkerur *et al.*, 2007), which is based on contextual filtering in Fourier domain. After enhancing the image, binarization is implemented to transform the enhanced image into a binary image. It

changes the pixel value into black for ridges and white for furrow. In addition, by improving the contrast between ridges and furrows. There are three main approaches in binarization (Meenen and Adhami, 2005): Global approach, neighbourhood-based approach and filter-based approach. In this study, local adaptive thresholding which based on neighbourhood-based approach is used because it has fast speed, good robustness and low complexity. Furthermore, the segmentation is implemented to eliminate the area near the boundary and area that does not have ridges.

The last process in pre-processing is thinning. Thinning is a process to change the pixel value into almost one (Xie and Lam, 1992). It reduces the thickness of the lines as much as possible with minimum loses. In thinning process, there are several processes, such as: (i) The output line should be a single pixel, (ii) the output line should not have any discontinuity, (iii) the output line should return to the centre pixel and (iv) eliminate the redundant line and unwanted pixels.

Minutiae Extraction

Crossing Number (CN) technique is implemented for the minutiae extraction process. The minutiae are detected by analysing the nearby neighborhood of every ridge pixel in the image by utilizing 3×3 window. The CN value is defined as half of the aggregate of the differences between the pairs of adjacent pixels in the eight-neighbourhood. Below is the formula to calculate the Crossing Number value:

$$CN = \frac{1}{2} \sum_{i=1}^8 |P_i - P_{i-1}|, P_9 = P_1 \quad (1)$$

where, P_i is the pixel value in the P neighbourhood.

After detecting the CN value, the pixel can be classified based on its CN value. In this fingerprint system, only ridge ending and bifurcation are extracted. The ridge pattern is called ridge ending if Crossing Number value is one and it is bifurcation if the Crossing Number value is 3.

Table 1. Comparison of Fusion levels

Level of Fusion	Strengths	Weaknesses
Data Level	Richest data information	Contain the most noise Hard to get
Feature Level	Contain more information compared with score and decision level Lesser noise compared with data level	Hard to implement when features set size are not same
Score Level	Easy to implement Less noise Most popular method	Less information compared with data and feature level
Decision Level	Easiest to implement Least information	

Post Processing

Not all minutiae detected from fingerprint image are real minutiae. By implementing post processing, false minutiae can be reduced. There are several steps to eliminate the false minutiae: Short breaks removal, spurs removal, H-points removal, close minutiae removal and border minutiae removal (Zhao and Tang, 2007): False minutiae can exist due to dirt, oiliness and scanner issues.

Matching

Before matching the testing fingerprint with template fingerprint, alignment process needs to be implemented because the fingerprint position might be different. In addition, the robustness of the fingerprint recognition can be improved. In this study, Affine transformation is used to uniformly the distorted fingerprint image. Moreover, affine transformation transforms the variable into a new variable by using a combination of rotation, translation, scaling and shearing. Below is the formula to define the affine transformation.

In matching process, the minutiae features from the template are compared with the query minutiae features. In this stage, Modified Hausdorff Distance (MHD) is implemented. MHD is basically based on the Hausdorff Distance. Originally, this method has been proposed by (Dubuisson and Jain, 1994) for object matching and they determine the best distance measure based on the presence of noise. Compared to the original Hausdorff distance, MHD is more robust because by considering the average of the single distance, the effect of noise can be minimized.

Face Recognition

Similar to fingerprint recognition, face images need to go through several processes before matching process. In this study, feature based face recognition is chosen as it is more robust compared with holistic based. In addition, a new method that combined Local Binary Pattern (LBP) and Scale Invariant Feature Transform (STFT) is introduced. This proposed method uses LBP to enhance the image before feature extraction is done by SIFT.

Pre-processing

The first step in pre-processing is face detection. In this study, face detection is done by using Haar feature-based cascade classifier which introduced by (Viola and Jones, 2001).

Next, the face image color is changed into grayscale image and LBP is performed to enhance the face image. In LBP method, if the neighbour pixel has a higher value than a center pixel, it will become one and if less than the center pixel, the pixel value will become 0. After that, the value of the center pixel can be obtained by

concatenating the eight neighbour pixel values. In this research, LBP is utilized to improve the image in light of its robustness and straightforwardness to monotonic gray-scale changes caused by illumination variations.

Feature Extraction

Scale Invariant Feature Transform (SIFT) is performed to extract the unique features from the enhanced image. This method is a feature based method and it is invariant to scale and rotation. There are four main steps in SIFT: Scale Space Extrema Detection which uses Difference of Gaussian, Keypoint localization which eliminates the weak keypoints, orientation assignment to make the keypoint invariance to rotation and keypoint descriptor.

Matching

After extracting the SIFT features, the matching process is performed. The best candidate match for each keypoints is obtained by finding its nearest neighbour in the keypoint database. In addition, the nearest neighbour is defined as the keypoint with the minimum Euclidian distance for the invariant descriptor vector. Furthermore, by comparing the closest neighbour distance with the second closest neighbour, the matching process can be more effective.

Score Level Fusion

Score level fusion is the fusion in matching score level. Therefore, it is additionally called matching level fusion (Cui and Yang, 2011; Jhansi and Reddy, 2015). In this research, the score level fusion is used to combined the matching score from fingerprint and face recognition. In addition, the extracted feature set of fingerprint and face are different so it is easier to fuse the information in score level. In this study, the score need to be normalized before fused together.

Score Normalization

In this study, Min-Max normalization is used for score normalization. Min-max normalization normalizes the scores to interval [0,1]. The normalized scores is calculated as follow:

$$x' = \frac{x - \min(X)}{\max(X) - \min(X)} \quad (2)$$

where, $\min(X)$ and $\max(X)$ are the minimum and maximum values of the matching scores (Jain *et al.*, 2005).

Sum Rule

Sum rule-based is performed to combined normalized fingerprint and face scores. The fused score is obtained by using the following formula:

$$f_s = x_1 + \dots + x_m \quad (3)$$

In this research, weighted sum-rule is used. In weighted sum-rule, weight is added to the matching score so that the score can be set based on the weight. Below is the formula to calculate the weighted sum-rule:

$$f_s = w_1x_1 + \dots + w_mx_m \quad (4)$$

where, $w_1 + w_2 = 1$. Moreover, w_i is the weight which assigned to the normalized score (x_1, \dots, x_m) .

Experimental Results and Discussion

Dataset and Experiment Setting

In this experiment, three fingerprint databases and two face databases were used. In addition, there are three combined databases that used to test the fusion performance. The detail of each database is explained in each subsection.

Fingerprint Databases

The fingerprint databases used in this experiment are FVC2002 DB1 database refers as FingerDB1 and FVC2002 DB2 database refer as FingerDB2. Each

database consists of 100 person with 8 different fingerprint impression for each person. In total, there are 800 fingerprint images for each of database. FVC2002 DB1 database was collected using optical sensor “TouchView II” by Identix. Moreover, the image size is 388×374 with a resolution of 500 dpi. In addition, FVC2002 DB2 database was collected using optical sensor “FX2000” by Biometrika. The image size is 296×560 and the resolution is 569 dpi.

In addition, SDUMLA-HMT fingerprint database refers as FingerDB3 is used as well (Yilong *et al.*, 2011). This database comprises of unique finger impression pictures from the index finger, middle finger and thumb finger of both hands. Furthermore, fingerprint images are captured by 5 different fingerprint sensor, such as AES2501 fingerprint scanner created by AuthentecInc, FPR620 optical finger impression scanner which created by ZhongzhengInc, URU4000 optical unique finger impression scanner created by ZhongkongInc and ZY202-B optical fingerprint scanner created by Chuba Academy of Sciences. There are 8 impressions captured for each of 6 fingers so the total images in the database are 106 subjects $8 \times 6 \times 5 = 25,440$ fingerprint images. Every fingerprint images in this database are saved in gray-level “bmp” format.

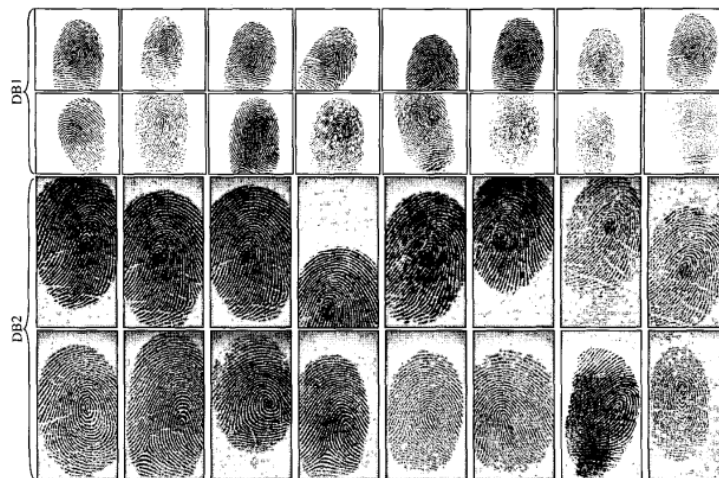


Fig. 1. FVC2002 DB1 and DB2 fingerprint database



Fig. 2. SDUMLA-HMT fingerprint database

In addition, Fig. 1 shows the fingerprint sample from FVC2002 DB1 and DB2 fingerprint database and Fig. 2 shows the fingerprint sample from SDUMLA-HMT Database.

Face Databases

There are two face databases that used for this experiment which is FERET database refer as FaceDB1 and SDUMLA-HMT refer as FaceDB2 (Yilong *et al.*, 2011). These two databases were chosen because both of database consist of face images from more than 100 persons. The FERET database contains 1564 sets of images for a total of 14,126 images from 1199 persons and 365 duplicate sets of images (Delin *et al.*, 2015). The Face Recognition Technology (FERET) program is conducted by the Defense Advance Research Project Agency (DARPA) and the National Institute of Standard and Technology (NIST). Figure 3 shows some sample images from FERET database.

Another database used in this experiment is SDUMLA-HMT face database. Figure 4 shows some sample images from SDUMLA-HMT database. This face database is collected with various poses, accessories, illumination and facial expression from 106 persons. Similar with FingerDB3, this database was created by Shendong University in 2010. In this study, only 800 face images from 100 persons are used. The original size of the image is 620×480 pixels. In this experiment, the detected face is cropped to 60×90 pixels.

Fingerprint Matching using Modified Hausdorff Distance

In this experiment, the fingerprint image was enhanced using STFT and the fingerprint feature was

extracted using Crossing Number Technique. In addition, in point based matching, fingerprint alignment is very important as the finger position is different from one finger with another finger. In this study, an affine transformation is implemented. The affine transformation is used for rotation and translation purpose. For the rotation, the features are rotated from 0 until 360 degrees and translated from 0 until 10 point to find the closest match. In addition, MHD is used for fingerprint matching purpose.

Table 2 shows the difference between fingerprint matching using MHD with and without using alignment method on FingerDB1. As shown in Table 4, the EER with affine transformation is 18.55%. Furthermore, on FingerDB2, the EER before alignment process is 39.64% and after implementing affine transformation, the EER can be reduced to 27.47%. Lastly, the EER before alignment process on FingerDB3 is 28.79% and the EER can be reduced to 14.47% after implementing affine transformation.

Based on the experiment result, the alignment process especially affine transformation is very important in point based fingerprint matching. In addition, compared with other distance matching method, MHD is more robust as it uses the average of the single distance, the effect of noise can be minimised.

Face Recognition using LBP-SIFT

In this research, face features are extracted using three different methods: SIFT, LBP-SIFT and SURF. The intention of this experiment is to compare and verify that the proposed method has better result compared with the similar methods.



Fig. 3. FERET database



Fig. 4. SDUMLA-HMT face database

Table 2. Performance comparison

Database	EER (%)	
	MHD	MHD with affine transformation
FingerDB1	30.38	18.55
FingerDB2	39.64	27.47
FingerDB3	28.79	14.47

Table 3. Face recognition on FaceDB1

Method	EER
SIFT	16.4170
LBP-SIFT	10.8030
SURF	24.5695

Table 4. Face recognition on FaceDB2

Method	EER
SIFT	13.930
LBP-SIFT	13.161
SURF	29.360

Table 5. Score fusion

Databases	EER (%)
FaceDB1+FingerDB1	7.83
FaceDB1+FingerDB2	9.13
FaceDB2+FingerDB3	7.01

Table 3 shows the face recognition method comparison on FaceDB1. SURF can achieve EER 24.569% and EER for original SIFT and LBP-SIFT are 16.417 and 24.5695% respectively.

In addition, Table 4 shows the EER comparison between SIFT, LBP-SIFT and SURF, on FaceDB2. Based on above table, SURF which is another point based method only can achieve EER 29.36%. Meanwhile, LBP-SIFT can achieve EER 13.161%. Based on Table 4 and 3, LBP-SIFT has a better performance compared with original SIFT and SURF.

Fusion

The score level fusion is used to combined the matching score from fingerprint and face recognition. Here, Sum rule-based analysis is performed to combined normalized fingerprint and face scores.

Table 5 shows that there are three scenarios that used in this experiment. The first database combination is FaceDB1 with FingerDB1, the second combination is FaceDB1 with FingerDB2 and the last is FaceDB2 with FingerDB3. The first two combinations consist of fingerprint and face images, not from the same person and the last combination is the database that collected from the same person. In addition, the EER score for fingerprint recognition is taken from MHD+affine transformation method and the EER score for face recognition is taken from LBP-SIFT method.

The first scenario can achieve EER 7.83%, the second scenario is 9.13%. The second scenario has a lower performance because FingerDB2 is more complex

than FingerDB1. Lastly, the third scenario can achieve EER 7.01%. These results are obtained after min-max normalization followed by the sum-rule method to combine the matching score.

Conclusion

In this research, we have presented a new approach for multimodal biometric using fingerprint and face recognition on score level fusion. From our findings, the fingerprint recognition, MHD along with the use of affine transformation can improve the accuracy performance. In addition, LBP-SIFT has shown better performance than original SIFT and SURF. Furthermore, by combining fingerprint and face recognition, the EER score can be greatly improved. Therefore, the experimental result shows that our proposed fusion method appears to be promising with 7.01~9.13% of EER based on different datasets.

Author's Contributions

All authors equally contributed in this work.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of other authors have read and approved the manuscript and no ethical issues involved.

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