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Development of Multibiometric Verification System Based on Speech and Palm Print Information

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ABSTRACT

Biometrics is science and technology of measuring and analyzing biological data. But, unibiometrics systems are prone to be lack of accuracy, non-universality and spoof attacks. However, these limitations can be minimized by developing a multibiometric system. Biometric fusion is the combination of information from multiple sources of sensors, modalities or biometric algorithms. In this project, a multibiometric based on speech and palm print information is developed. In speech biometric system, Mel Frequency Cepstrum Coefficient (MFCC) and Linear Predictive Coding (LPC) techniques are used to extract audio features while Region of Interest (ROI) is used to extract visual features of palm print. In pattern-matching, Support Vector Machine (SVM) is used as classifier. Subsequently, for multibiometric system, score level fusion with sum-rule fusion and weighted sum-rule fusion techniques are used to increase the system performances. Receiver Operation Characteristic (ROC) curve of Genuine Acceptance Rate (GAR) versus False Acceptance Rate (FAR) is plotted and Equal Error Rate (EER) is calculated to evaluate the performance of the biometric systems. Lastly, the multibiometric system is developed by using GUI. In this project, it has been proven that the multibiometric system with MFCC technique together with the weighted sum-rule score fusion gives the best performance with the lowest EER percentage i.e. 0.2046% compared to 2.1678%, 1.0088% and 6.8515% for single biometric system based on MFCC, LPC and palm print.

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INTRODUCTION

Information technology field becomes advance and widely used nowadays. As the internet becomes common for information exchange, hence a reliable authentication system is very important to ensure its privacy and confidential. The applicability of traditional methods such as pin identification, password or token based (ID cards) arrangement has many limitations and restricted. Furthermore, password or pin identification can be lost, forgotten or stolen. As a consequent, biometrics approach has become a good alternative for the identity authentication due to its uniqueness to each individual and cannot be lost, recreated or forgotten (Teoh *et al*., 2003, Bhattacharyya *et al*., 2009).

Biometrics is the science of measuring human's characteristics for the purpose of authenticating or identifying the identity of an individual. There are two main classes in biometric characteristics which are physiological characteristic and behavioral characteristic. Physiological characteristic is a biometric feature that measures the parts of body and it varies from person to person. The examples of physiological characteristics are face recognition, palm print, hand geometry, fingerprint and iris recognition. On the other hand, behavioral characteristic measures the action that is performed by human such as signature and voice (Yih *et al*., 2008).

However, unibiometric systems are prone to be affected by problems such as lack of accuracy, non-universality, noise sensor data and spoof attacks due to its identifier only use single source of biometric information. These limitations of the unibiometric systems can be reduced by combining multiple sources of biometric information. Accordingly, a system which consolidates information from multiple sources i.e.multibiometric systems are developed in order to enhance the accuracy and the performance of unibiometric systems (Kisku*et al*., 2011). The performance of multimodal biometric system can be increased by information fusion as reported in (Liau and Isa, 2011).

Multimodal biometrics can overcome the limitations possessed by single biometric trait and

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give better classification accuracy (Ross and Jain, 2003).This paper proposes an audio-visual system based on fusion at matching score level using support vector machine (SVM). The support vector machine-based fusion method also gave very promising results. Speech biometrics is proposed in this research due to the ease of data collection which is natural and non-obstructive. Furthermore, the hardware used is cost effective and only a simple arrangement is needed for setting up for the data collection process.

Subsequently, the advantages of the use of palm print biometrics are large palm area for feature extraction is available, easy of capturing and high user acceptability (Sun *et al*., 2005). The cost of palm print acquisition device is less compared to other biometric trait like iris and fingerprint scanning device. Besides, palm print is harder to imitate than fingerprint. It is more acceptable than face recognition system that may cause privacy issues (Shu and Zhang, 1998). As reported in Kong (2000), human palm has line features including minutiae points as in the case of fingerprints. In order to obtain the palm features, the palm can be scanned so as to get an abundance of ridges and minutiae information which form the finer details of the palm. In this research, these finer details are obtained by scanning the palm image a high resolution of 1000 DPI. In Ibrahim and Ramli (2013), instead of focusing on the final details, the higher level textural information presents on the palm in the form of major lines and small wrinkles are extracted. The reason for choosing to work with these features is that the higher level details can be captured by using a generic web camera at low resolution (Ibrahim *et al*, 2014).

Methodology:

The methodology in this study is divided into 4 modules i.e. data acquisition, feature extraction, classification, fusion and development of GUI for the developed palm print biometric system.

Data Acquisition and Feature Extraction:

a. Speech Biometric:

This database consists of the digitized speech signals of the recording voices of 37 speakers stored as monophonic 16 bit, 32 kHz and in WAV format. There are 60 audio data for each speaker obtained. Hence, it consists of 2220 data. A speaker verification system is developed by using mel-frequency cepstral coefficients (MFCC) and linear predictive coding (LPC) as feature extraction and SVM as classifier

MFCC processing consists of signal pre-emphasis, windowing, spectral analysis, filter bank processing, log energy computation and mel frequency cepstrum computation as shown in Fig. 1. There are 12 melcepstrum coefficients, one log energy coefficient and three delta coefficients per frame have been set in the experiments.

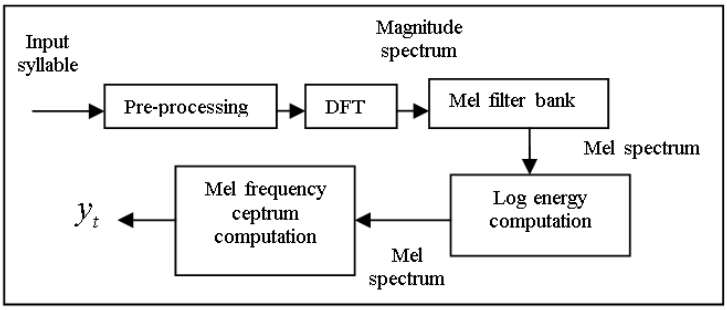

Fig. 1: Typical MFCC process

On the others hand, LPC feature extraction models the process of speech production and is defined as a digital method for encoding an analogue signal in which a particular value is predicted by a linear function of the past values of the signal (Rabiner & Juang, 1993; Furui, 1981) where the process of the LPC is shown in Fig. 2.

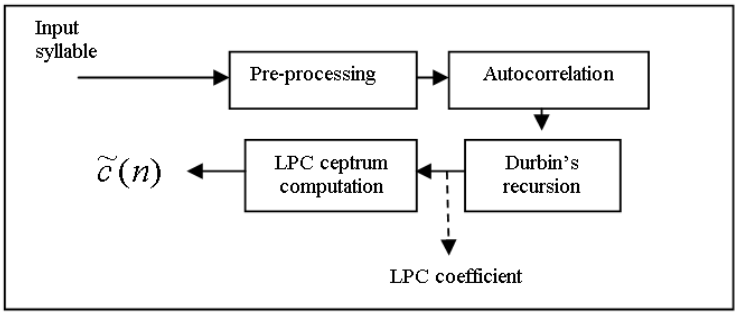

Fig. 2: Typical LPC process

b. Palm print Biometric:

Palm print database contains 60 images right hand images collected from 37 individuals by using Canon optical scanner. The acquired images of palm print are in BMP format. Each speaker consists of 60 sequences of palm print images (20 sequences from each session) hence in total of 2220 images from entire speakers. The visual data of 2220 images from 37 speakers are converted into gray scale with the size of 351 x 351 pixels. The gray scale images are stored for the feature extraction process. For each speaker, first 20 images are selected as model or training set, and then the rest 40 images of each speaker in this database are used in verification system or testing set. Hence, there are 740 data are stored in training set and 1480 data as testing set.

The ROI of palm print image with gray scale level is used as features in this study. The appropriate coordinate is chosen on the palm print image in order to crop the image that contains the principal lines. A region of ROI is determined to get the cropped image.

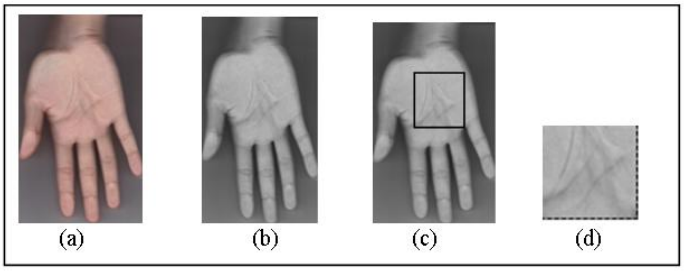

Fig. 3: Extraction of palm print biometric modality (a) Acquired image from scanner (b) Gray scale level of palm print image (c) ROI region to be cropped (d) Cropped image

Pattern Matching:

After extracting features from the speech signal and palm print images, the features are fed to the classifier and proceed with the pattern matching process. In pattern matching process, the similarity of the testing data and training data is measured.

In SVM classifier, 20 data of each speaker is used as the training data and 40 data of each speaker is used as testing data. The SVM classifier calculates the score of the pattern matching between training data and testing data. Several sets of parameters are determined in polynomial Kernel to compare the performance of the system. Consequently, the FARs, GARs and EERs values are calculated and the ROC curve is plotted in order to evaluate the performance of the multibiometric system.

$$Scorefusion = w_1.score_{speec\,h} + w_2.score_{palmprint} \quad (2)$$

$$w_1 + w_2 = 1 \quad (3)$$

The weights, w_1 and $w_2$are varied from range of 0.1 to 0.9 in steps 0.1. ROC curve based on the new set of fusion scores is plotted to analyze the system performances.

GUI development:

Finally, a GUI of multibiometric system is developed. GUI is a visual object that enhances interaction between a computer and a user. The GUI layout is designed so as to support the process of data collection, user-friendly between users and interface as well as to assist administrative work.

Score Fusion:

After pattern matching via SVM classifier is executed, the scores obtained from two single biometric systems which are speech biometrics and palm print biometrics will proceed to fusion task. The score fusion techniques used in this study are sum rule technique and weighted sum-rule technique.

In sum rule technique, the new set of score is obtained as shown in Eq. (1).

$$Scorefusion = \frac{score_{speec\,h} + score_{palmprint}}{2} \quad (1)$$

The combined matching score can also be computed as a weighted sum-rule as given in the Eq. (2) and Eq. (3).

RESULTS AND DISCUSSION

To evaluate the performance of the system, a ROC curve of GAR versus FAR is plotted. A total of 1,480 genuine data (40 genuine data from each speaker) and 53,280 imposter data are used to plot the ROC curve. Several ROC curves are plotted to compare the performances of single biometric system and multibiometric system which have been undergone the score fusion.

FAR is the percentage of wrongly accepted individuals over the total number of wrong matching. FRR is the percentage for number of wrongly rejected individuals over the total number of correct matching. GAR is the percentage of the number of correctly accepted individuals divided by the number

of identification attempts. EER is the value when FAR is equal to FRR.

Performances for Single Biometric System:

Fig. 4 shows the ROC curve for three distinct cases in single biometric systems, (i) speech biometrics with LPC features, (ii) speech biometrics with MFCC features, and (iii) palm print biometric system with ROI features. When FAR is 1%, the GAR values of palm print system with ROI features, speech system with LPC features and speech system with MFCC features are 80%, 95% and 99% respectively. When FAR achieves 10%, speech biometrics with LPC and MFCC features approximately approach 100% of GAR where palm print biometrics with ROI features is 95%. Table 1 indicates the EER performances for three different biometric systems. Palm print biometrics with ROI features has the highest value of EER where speech biometrics with MFCC features has the lowest value of EER.

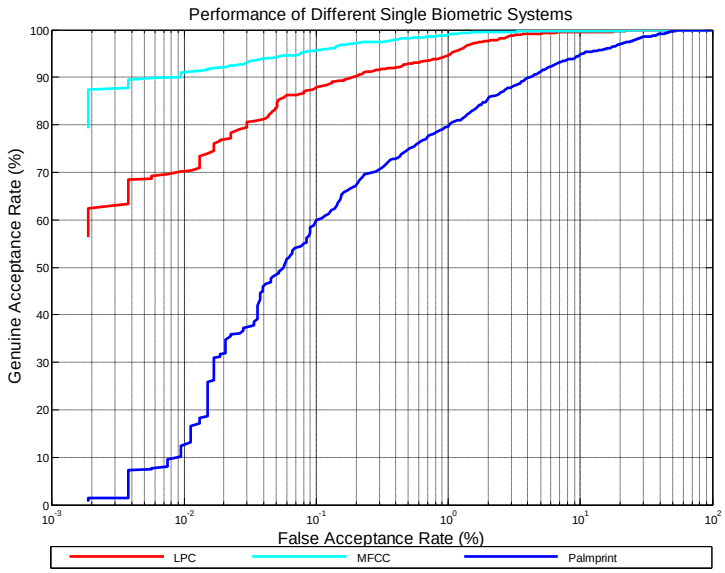

Fig. 4: Comparison of ROC curves of speech biometric and palm print biometric

Table 1: EER percentages for single biometric systems

LPC	MFCC	Palm print
2.1678	1.0088	6.8515

Performances for Sum-Rule Fusion of Multibiometric Systems and Single Biometric System:

Fig 5 shows the ROC curves of sum-rule score fusion of multibiometric system with different single biometric system (a) speech biometrics with LPC features; (b) speech biometrics with MFCC features and (c) palm print biometrics with ROI features. When FAR is 0.1%, the GAR value of LPC and palm print sum-rule score fusion is 98%. For MFCC and palm print sum-rule score fusion, the GAR percentage is 99%. When FAR is 1%, the GAR values of score fusion of speech biometrics with LPC features and palm print biometrics is achieved 99.5%. Else, the GAR values of score fusion of speech biometrics with MFCC features and palm print biometrics is 100%. Table 2 shows the EER performances of single biometric system and multibiometric system with sum-rule score fusion. The multibiometric system with combination of speech biometrics with MFCC as features and palm print biometrics with ROI features has the smallest value of EER. Hence, the fusion multibiometric system has the higher performance than the single biometric system.

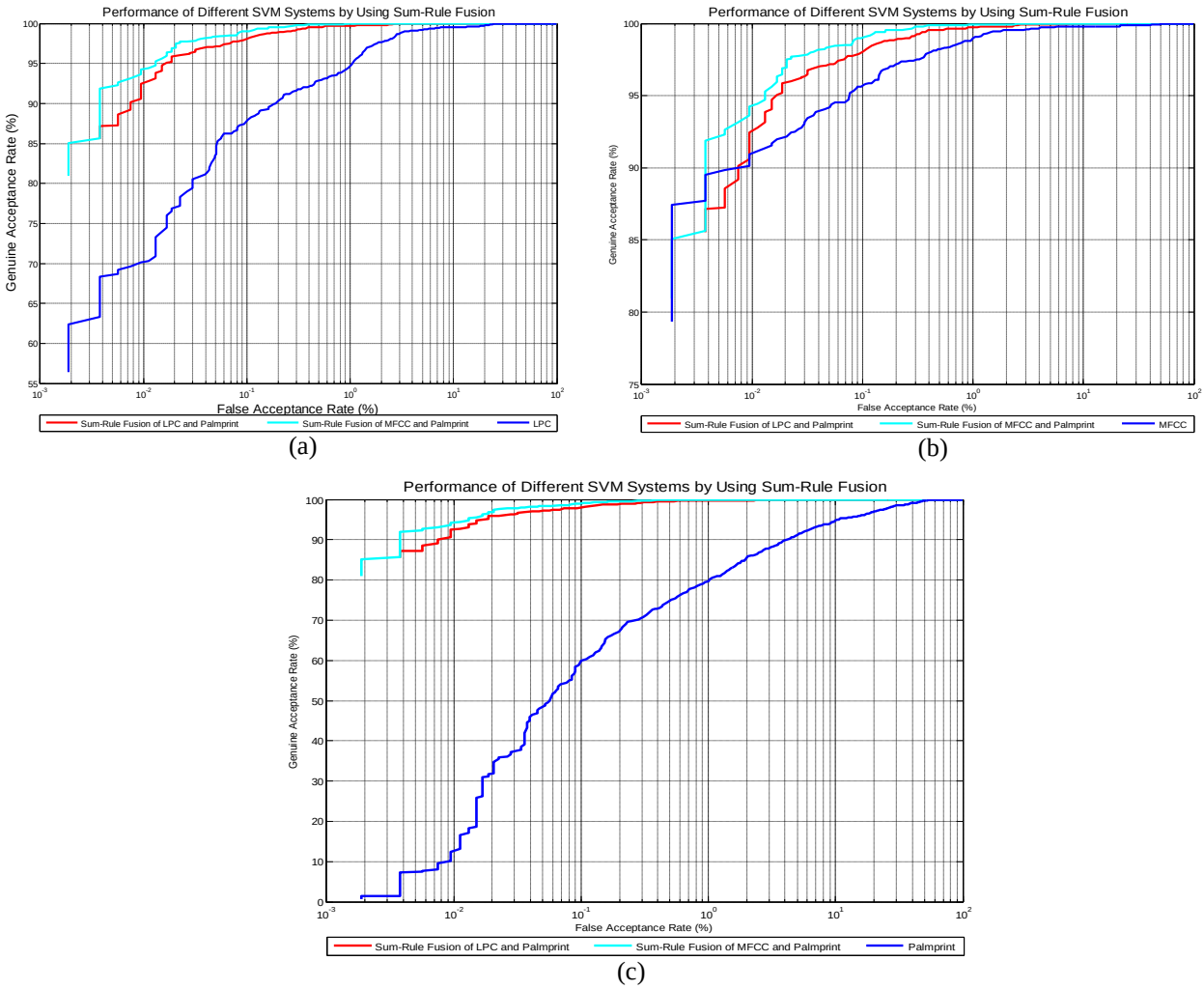

Fig. 5: Comparison of ROC curves of sum-rule score fusion of multibiometric system with respective single biometric system (a) speech biometrics with LPC as feature extraction, (b) speech biometrics with MFCC as feature extraction and (c) palmprint biometrics

Table 2: EER percentages for single biometric system and multibiometric system

LPC and Palm print	MFCC and Palm print	LPC	MFCC	Palm print
0.4673	0.3087	2.1678	1.0088	6.8515

The intersection point of the FAR and FRR rate in the multibiometric system (speech biometrics with LPC feature and palm print biometric system) by using weighted sum-rule score fusion is 0.4730 which represents EER rate for the system as shown in Fig. 6. The desired threshold value obtained is 0.7469.

Fig 7 shows the FAR and FRR percentages with different threshold values for weighted sum-rule fusion of speech biometric system with MFCC feature and palm print biometric system. The intersection point of the FAR and FRR rate is 0.2027 which represents EER rate for the system. The desired threshold value obtained is 0.7175.

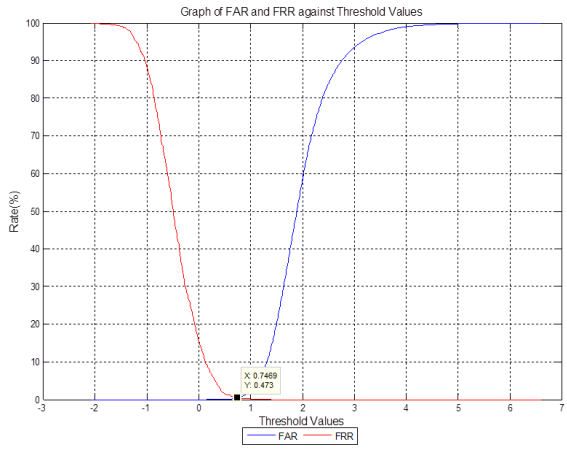

Fig. 6: Graph of FAR and FRR percentages versus different threshold values of multibiometric system (weighted sum-rule fusion of speech biometrics with LPC feature and palm print biometrics)

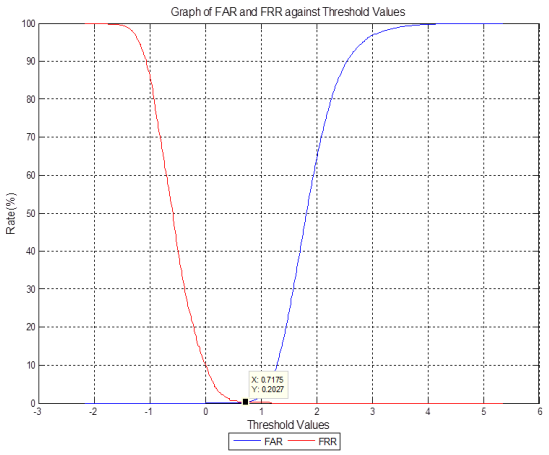

Fig. 7: Graph of FAR and FRR percentages versus different threshold values of multibiometric system (weighted sum-rule fusion of speech biometrics with MFCC feature and palm print biometrics)

Implementation of GUI:

A GUI for multibiometric system as shown in Fig 8 is developed to increase the user friendliness. First of all, the user needs to key in their ID and press the enter button. Once the valid ID is obtained by the system, the system will proceed to the next step. The user can choose either speech biometrics, palmprint biometrics or both as shown in Fig 8(a). Next, the system requests for the biometric trait(s) enrollment. For this case, the user enrolls his/her biometric trait(s) by browsing the database. The enrolled biometric trait will pop up as in Fig 8(b). After the system obtains the enrolled biometric trait(s), the user can choose the types of feature extraction to be used in the system. In speech biometric system, there are two available feature extraction techniques which are MFCC and LPC. In palmprint biometric system, the feature extraction technique used is ROI. After the feature extraction, the system will match the enrolled trait with the model by using SVM classifier. Fig 8(c) indicates the pattern matching in process. Once the score is obtained, the system will proceed to decision. If the score is below the threshold value, the system will show accept as in Fig 8(d), else the system will show reject which means that user is an imposter.

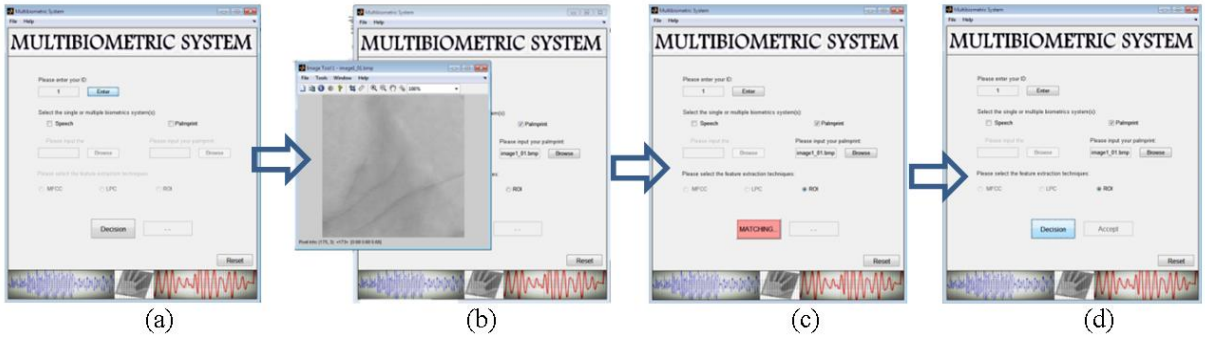

Fig. 8: Layout of the GUI

Conclusion:

At the end of this research, a reliable multibiometric system is successfully developed. Based on the analysis result, weighted sum-rule score fusion of multibiometric system has the best performance. These projects successfully develop 2 single modal systems based on speech and palm print using SVM classifier. Speech biometric system and palm print biometric system are developed for verification. SVM classifier is used during the pattern-matching process. Palm print biometric system has the lowest performance compared to speech biometric system. Next, a multibiometric system is developed by combining the speech and palm print biometric. Score level fusion is applied to obtain a better performance of the system. In this project, the score level fusion techniques used are sum-rule fusion and weighted sum-rule fusion. The performance of the system is analyzed by plotting

ROC curve. The sum-rule fusion has the best performance.

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