ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 1, January 2015

A Novel Approach on Signal Biometric Identification System- Using the Fusion of Palmprint and Speech Signal

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ABSTRACT: Biometric systems allow automatic person recognition based on physical or behavioral features which belong to a certain person. Each biometric feature has its limits and no biometric system is perfect so unimodal biometric systems raise a variety of problems. To over fulfilling some of the mentioned inconvenient and limitations and to increase the level of security the multimodal biometric systems are used. This paper proposes the multimodal biometrics system for identity verification using two traits, i.e., speech signal and palmprint. The proposed system is designed for applications where the training data contains a speech signal and palmprint. The matching score level architecture uses weighted sum of score technique. The features are extracted from the pre-processed palm image and pre-processed speech signal. The features of a query image and speech signal are compared with those of a database images and speech signal to obtain matching scores. The individual scores generated after matching are passed to the fusion module. This module consists of three major steps i.e., normalization, generation of similarity score and fusion of weighted scores. The final score is then used to declare the person as genuine or an impostor. The system is tested on database collected by the authors for 120 subjects and gives an overall accuracy of 98.63% with FAR of 1.67% and FRR of 0.84%.

KEYWORDS: Biometrics; multimodal; speech signal; palmprint; fusion; matching score.

I. INTRODUCTION

Biometrics based personal identification is getting wide acceptance in the networked society, replacing passwords and keys due to its reliability, uniqueness and the ever in-creasing demand of security. Common modalities being used are fingerprint and face but for face authentication people are still working with the problem of pose and illumination invariance where as fingerprint does not have a good psychological effect on the user because of its wide use in crime investigations. If any biometric modality is to succeed in the future it should have the traits like uniqueness, accuracy, richness, ease of acquisition, reliability and above all user acceptance. However, unimodal biometric systems which use a single trait for authentication, will suffer from problems like noisy sensor data, non-universality, lack of distinctiveness of the biometric trait, unacceptable error rates, and spoof attacks. These problems can be tackled by using multi-biometrics in the system. Multi-modal biometric technology which can use complementary information between different modals to improve the recognition rate has four levels, data level [1-3], feature level [4-6], score level [7-8] and decision level [9-10].This paper focuses on the integration of score level.

This paper proposes, multimodal biometric system using two traits, i.e. palmprint and speech signal. The proposed system is designed for applications where the training data contains a palmprint and speech signal. Integrating the palmprint and speech features increases robustness of person authentication. The final decision is made by fusion at matching score level architecture in which feature vectors are created independently for query measures and are then compared to the enrolment templates, which are stored during database preparation.

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Wavelet-Based Kernel PCA method is used to extract feature for palmprint meanwhile Mel Frequency Cepstral Coefficients (MFCC) is used to extract features of speech signal. The matcher weights are calculated based on Equal Error Rate (EER) of the intended matchers for fusion, which significantly increases the accuracy of the recognition system.

The paper is organized as follows. Section 2 describes system structure. Section 3 describes the MFCC and Vector Quantization (VQ), Section 4 describes Wavelet based Kernel PCA, Section 5 describes proposed fusion technique, In Section 6, Experimental results are compared and discussed in this Section. Finally, conclusions and future work are given in Section 7.

II. SYSTEM STRUCTURE

The block diagram of a multimodal biometric system using two (palm and speech) modalities for human recognition system is shown in Fig. 1. It consists of three main blocks, that of Preprocessing, Feature extraction and Fusion. Preprocessing and feature extraction are performed in parallel for the two modalities. The preprocessing of the audio signal under noisy conditions includes signal enhancement, tracking environment and channel noise, feature estimation and smoothing [11]. The preprocessing of the palmprint typically consists of the challenging problems of detecting and tracking of the palm and the important palm features.

The preprocessing should be coupled with the choice and extraction of speech and palm features as depicted in Fig. 1. For the palmprint and speech signal, the input image is recognized using Wavelet-Based Kernel PCA method and MFCC with VQ respectively. The matching score for speech is calculated by Euclidean distance using code book.

Similarly the matching score for palmprint is calculated by Euclidean distance. The modules based on individual modality returns an integer value after matching the templates and query feature vectors. The final score is generated by using the matcher weighting based on EER and weighted product technique at fusion level, which is the passed to the decision module. The final decision is made by comparing the final score with a threshold value at the decision module.

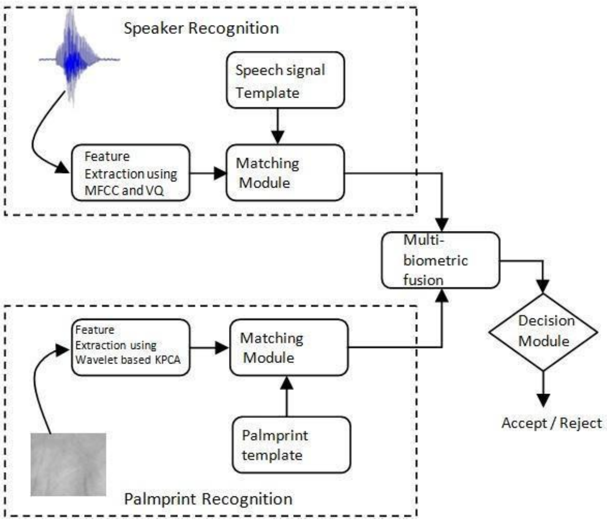

Fig. 1 Block diagram of the proposed multimodal biometric verification system

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III. ALGORITHM OF CALCULATION OF SPEECH FEATURES

USING MFCC

The MFCC cepstrals in speech recognition system is used for calculating speech features. Calculation of the speech features algorithm is defined by several process as in the following form.

1. Pre-processing. The amplitude spectrum of a speech

passed through a first-order FIR high pass filter:

$$s_p(n) \quad s_{in}(n) \quad .s_{in}(n \; 1) \qquad (1)$$

where is the filter coefficient ((0.95;1)), s_{in} (n) is the input signal.

2. End Point Detection (EPD). This helps to locate the endpoints of an utterance in a speech signal. An inaccurate endpoint detection will decrease the performance of the speech recognizer. Some commonly used measurements for

finding speech are short-term energy estimate E_s , or short

term power estimate P_s , and short term zero crossing rate

Z_s .For the speech signals $s_p(n)$ these measures are calculated as follows:

$$Z_s(m) \quad \frac{1}{L} \quad \overset{m}{\underset{n \, m \, L \, 1}{}} \quad \frac{\operatorname{sgn}(s_p(n)) \; \operatorname{sgn}(s_p(n \; 1))}{2} \qquad (2)$$

1, $s_p(n)$ 0, sgn($s_p(n)$)
1, $s_p(n)$ 0.

where these measures calculate the values for each block of L samples. The short term zero crossing rate gives a measure

of how many times the signal, $s_p(n)$, changes sign. This

short term zero crossing rate tends to be larger during unvoiced regions. This needs some decision to find the begin and end point. Some assumption is made to remove the background noise, i.e., removing first 5 blocks. To make this a comfortable approach, the following function is used:

$$W_s(m) \quad P_s(m).(1 \quad Z_s(m)).S_c \qquad (3)$$

where S_c is a scale factor. The trigger for this function can be described as:

$$t_w \quad _w \quad _w \qquad (4)$$

where $_w$ and $_w$ is the mean and variance.

where 0.4 (5)
=0.2 $_w$

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The end point detection function, EP$D(m)$, can be found as:

$$EPD(m) \quad \begin{matrix} 1, & W_s(m) \quad t_w & , \\ 0, & W_s(m) \quad t_w & \end{matrix} \qquad (6)$$

By using this function we can detect the endpoints of an utterance.

3. Framing. The input signal is divided into overlapping frames of N samples.

$$s_{frame}(n) \quad s_p(n).w(n), \qquad (7)$$

$$w(n) \quad \begin{matrix} 1, & K.r \quad n \quad K.r \quad N, r \quad 0,1,2,..., M \quad 1, \\ 0, & Otherwise \end{matrix}$$

where M is the number of frames, f_s is the sampling

frequency, t_{frame} is the frame length measured in time, and K is the frame step.

(8)

$$N \quad f_s \, .t_{frame}$$

4. Windowing. There are different types of window functions to minimize the signal discontinuities. One of the most commonly used for windowing is the Hamming window:

$$s_w(n) \quad 0.54 \quad 0.46\cos \frac{2(n \quad 1)}{N \quad 1} s_{frame}(n), 1 \quad n \quad N$$

5. Calculating of MFCC features:

Fast Fourier transform(FFT): Applying by FFT to windowing frames to calculate spectrum of frames.

$$bin_k \quad \left| \sum_{n \quad 1}^{N} s_w(n) e^{i(n \quad 1)k \frac{2}{N}} \right|, k \quad 0,1,2,..., N \quad 1 \quad (10)$$

Mel filtering: The low-frequency components of the magnitude spectrum are ignored. The centre frequencies of

the channels in terms of FFT bin indices ($cbin_i$ for the i -th channel) are calculated as follows:

$$Mel(x) \quad 2595lg\, 1 \quad \frac{x}{}, \qquad x \quad 700.\, 10^{\frac{mel}{2595}} \quad 1,$$

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$$f_{c_i} = Mel^{-1}\left(Mel(f_{start}) + \frac{Mel(f_s/2) - Mel(f_{start})}{NF+1}\, i \right), \quad i = 1,2,3,\ldots,NF-1$$

$$cbin_i = round\left(\frac{f_{c_i}}{f_s} N \right) \qquad (11)$$

where NF is the number of channels of filter.

The output of the mel filter is the weighted sum of the FFT magnitude spectrum values (bin_i) in each band. Triangular, half-overlapped windowing is used as follows:

$$fbank_k = \sum_{i=cbin_{k-1}}^{cbin_k} \frac{i - cbin_{k-1} + 1}{cbin_k - cbin_{k-1} + 1}\, bin_i + \sum_{i=cbin_k+1}^{cbin_{k+1}} \left(1 - \frac{i - cbin_k}{cbin_{k+1} - cbin_k + 1}\right) bin_i,$$

$$k = 1,2,\ldots,NF-1 \qquad (12)$$

Non-linear transformation:. The output of mel filtering is subjected to a logarithm function (natural logarithm)

$$f_i = \ln(fbank_i), \quad i = 1,2,\ldots,NF-1 \qquad (13)$$

Cepstral coefficients: X cepstral coefficients are calculated from the output of the non-linear transformation block.

$$C_i = \sum_{j=1}^{NF-1} f_j \cdot \cos\left(\frac{\pi \cdot i}{NF-1} (j - 0.5) \right), \quad i = 1,2,\ldots,20$$

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ISSN (Print): 2320-9798

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(14)

Cepstral Mean Subtraction (CMS: The channel effect is eliminated by subtracting the mel-cepstrum coefficients with the mean mel-cepstrum coefficients:

$$mc_j(q) = C_j(q) - \frac{1}{M}\sum_{i=1}^{M} C_i(q), \quad q = 1,2,\ldots,20 \qquad (15)$$

A. Vector Quantization

Vector quantization (VQ) is a lossy data compression method based on principle of block coding [12]. It is a fixed-to-fixed length algorithm. VQ may be thought as an aproximator. Fig. 3 shows an example of a 2- dimensional VQ.

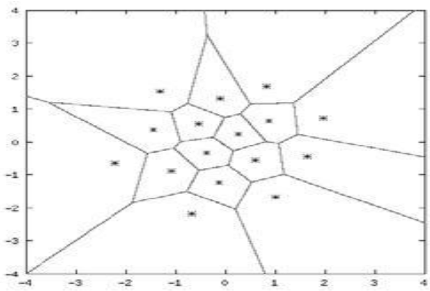

Fig. 2 An example of a 2-dimensional VQ

Here, every pair of numbers falling in a particular region are approximated by a star associated with that region. In Fig. 3, the stars are called *codevectors* and the regions defined by the borders are called encoding *regions*. The set of all codevectors is called the *codebook* and the set of all encoding regions is called the *partition* of the space [12].

IV. WAVELET BASED KERNEL PCA

A. Two-Dimensional Discrete Wavelet Transform

The 2-D DWT was applied to different applications given in the literature, e.g., texture classification[13], image compression[14], and face recognition[15,16], because of its powerful capability for multi resolution de-composition analysis. The wavelet transform is created by passing the image through a series of 2D filter bank stages. One stage is shown in Fig.2, in which an image is first filtered in the horizontal direction. The filtered outputs are then sampled by a factor of 2 in the horizontal direction. These signals are then each filtered by an identical filter pair in the vertical direction. Decomposed image into 4 subbands is also shown in Fig.2. Here, *H* and *L* represent the high pass and low pass filters[17], respectively, and 2 denotes the sub-sampling by 2. Second-level decomposition can then be conducted on the *LL* subband. This decomposition can be repeated for *n*-levels. The representation of one-level and two-level wavelet decompositions scheme is also shown in Fig.3.

In this study, we always select low frequency subimage LL for further decomposition. As explained in Fig.2, one-level wavelet transform can be extended to two-level, three-level variants, etc. In this work, we first extend the wavelet

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International Journal of Innovative Research in Computer and Communication Engineering

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transform to four-level. We then choose the lowest frequency subimage with a matrix of 16 × 16 as the feature vectors, referred to as *wavelet-palm*. Daubechies-8 high pass and low pass filters[17] are also implemented in this study. Consequently, the palmprint image with 128×128 is reduced to the subimage with 16×16. These parameters were empirically determined to achieve highest accuracies. Generally, low frequency components represent the basic figure of an image, which is less sensitive to varying images. These components are the most informative subimages gearing with the highest Discriminant power. Finally,M = features form a vector R^M, = (W_{00} , W_{01} , . . . , W).

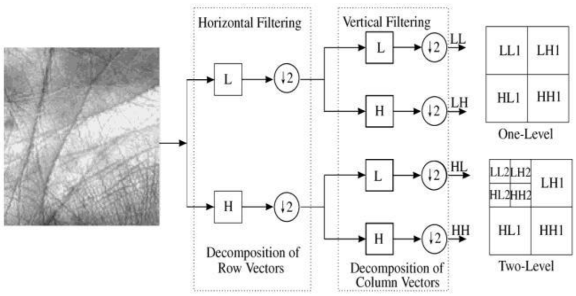

Fig. 3 One-level 2-D filter bank for wavelet decomposition and multi-resolution structure of wavelet decomposition of an image.

The most well-known discrete transform, DCT is employed in the proposed algorithm instead of DWT in order to examine the effects of each discrete transform. C (u, v) is the 2D-DCT coefficients of W×H image I(x, y), and is generated by using 2D-DCT technique. The palmprint image (128 × 128) in the spatial domain is not divided into any overlapped blocks. The DCT coefficients for the palmprint image are first computed. In the DCT, low frequencies corresponding to the 12.5% coefficients are also selected as useful features. Finally, N =μ × form a vector R^N = ($C_{0,0}$, $C_{0,1}$, . . . , C) for DCT.

The kernel PCA (KPCA) is an unsupervised technique that is based on the simple idea of performing Principal Component Analysis in the feature space of a kernel[18]. The input data is first mapped to a higher dimensional space by using a nonlinear operation (a kernel function). Linear PCA is then performed on the mapped data. On sequently, standard PCA can be applied in feature space to perform nonlinear PCA in the input space. Pair wise similarity between input examples is captured in a matrix K which is also called Gram matrix. Each entry $K_{i,j}$ of this matrix is calculated using kernel function k($_i$ $_j$). sum and being able to use the same type of perception in the coefficients determination. igenvalue equation in terms of Gram matrix is written as

= $K A$, (17)
with A = ($_1$ $_M$) and = $diag$($_1$ $_M$). A is an

M × M orthogonal eigenvector matrix and is a diagonal eigenvalue matrix with diagonal elements in decreasing order. Since the eigenvalue equation is solved for A instead of eigenvectors V_i of kernel PCA, we will have to normalize A to ensure that eigenvalues of kernel PCA have unit norm in the feature space, therefore $_j$ = $_{j\,j}$. After normalization the eigen-vector matrix, V, of kernel PCA is computed as follows:

$V = DA$ (18)
Where D = [($_i$) ($_2$) ($_M$)] is the data matrix in be a test example whose map in the higher dimensional feature space is ( ). The kernel PCA features for this example are derived as follows:

$F = V^{T}$ ( ) = $A^{T} B$, (19)
where B = [($_1$) (x) ($_2$) (x) ($_M$) (x)]^{T} .

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International Journal of Innovative Research in Computer and Communication Engineering

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B. Weighted Euclidean distance

The distance is calculated by similarity measurement. The weighted Euclidean distance was used for clustering the features and was defined as

$$d_k = \sum_{i=1}^{N} \frac{(f(i) - f_k(i))^2}{(S_k)^2} \qquad (20)$$

Where f is the feature vector of the unknown palmprint, f_k and s_k denote the k-th feature vector and its standard deviation, and N is the feature length.

V. FUSION

The different biometric system can be integrated to improve the performance of the verification system. The matcher weights are calculated based on Equal Error Rate(EER) of

using FAR and FRR. EER of matcher m is represented as

E_m , m W_m associated with matcher is computed as

$$W_m = \frac{\frac{1}{E_m}}{\sum_{m=1}^{M} \frac{1}{E_m}}, \text{ where } 0 \le W_m \le 1 \qquad (21)$$

The final score is calculated by weighted product approach. Logarithms were used to turn it into a weighted
Where log(F) is the final matching score.

VI. EVALUATIONS

The simulations are conducted on our own database. Database contains speech signal and palmprint images of 160 subjects. Each subject has 6 palm images taken at different time intervals and 6 different words, which is stored in the database. Before extracting features of palmprint, we locate palmprint images to 128x128. After fusion, we can achieve high genuine acceptance (98.2%) and a low false acceptance(0.01%) verification rates.

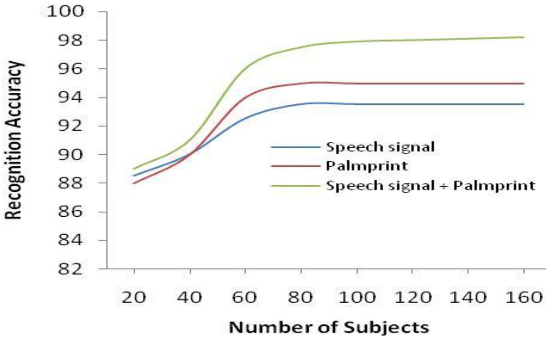

Fig. 4 Accuracy vs Subjects

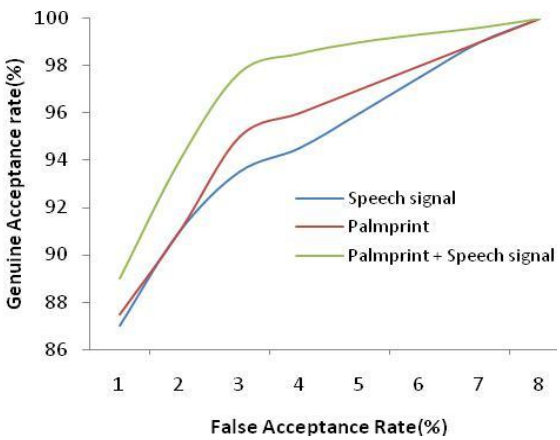

Fig. 5 Verification test results (GAR vs. FAR)

VII. CONCLUSION

This paper presents a new approach using palmprint and speech signal. Wavelet-based kernel PCA approach was used for palmprint feature extraction and Subband Decomposition via Wavelet Packets was used for Speech signal feature extraction. A novel fusion scheme based on GMM and Weighted Euclidean distance for the fusion of palmprint and speech signal is proposed and experimentally tested on our database. Experimental results demonstrate the effectiveness of the proposed approach for multimodal authentication using palmprint and speech signal.

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