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PEA: Parallel electrocardiogram-based authentication for smart healthcare systems

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ABSTRACT

Currently, ECG-based authentication is considered highly promising in terms of user identification for smart healthcare systems because of its inimitability, suitability, accessibility and comfortability. However, it is a great challenge to improve the authentication accuracy, especially for scenarios that include a large number of users. Thus, this paper proposes a parallel ECG-based authentication called PEA. Specifically, this paper proposes a hybrid ECG feature extraction method that integrated fiducial- and non-fiducial-based features to extract more comprehensive ECG features and thereby improve the authentication stability. Furthermore, this paper proposes a parallel ECG pattern recognition framework to improve the recognition efficiency in multiple ECG feature spaces. Through the experiments, the performance of the proposed authentication is verified.

1. Introduction

To improve the degree of certain qualities or attributes, such as availability, privacy, reliability, safety, security, and their nonintelligent counterparts, smart healthcare systems focusing on these qualities are intended to improve health outcomes, reduce costs, and enhance the quality of life (Laplante et al., 2016; Gravina and Fortino, 2016). Because these systems involve various sensitive information, such as medical data and privacy records, it has become an indispensable task to safeguard the security and privacy of smart healthcare systems (Li et al., 2016). Therefore, various authentication methods have been proposed to protect user privacy and security.

It is now widely recognized that biometrics are more reliable than knowledge- and possession-based approaches such as identity cards and usernames/passwords because for biometrics, there is no need to remember anything. Biometric attributes cannot be lost, transferred or stolen, and they offer better security because these attributes are very difficult to forge and require the presence of a genuine user to grant access to particular resources (Unar et al., 2014). Therefore, the biometric-based approach is considered to play a critical role in balancing privacy with performance (Dantcheva et al., 2016). Generally, biometrics are divided into the following two categories:

1. **Behavioral Biometrics** are often implemented on mobile and wearable devices to identify users by gesture, touch dynamics, keystroke, etc. (Abate et al.,; Bo et al., 2013). Generally, behavioral biometrics are used to prevent inside attacks, but they have also been deemed valid for entry into a system (Manning, 2017). Hence, some advanced biometrics involving more behavioral information are proposed to provide better authentication (Peng et al., 2017).
2. **Physiological Biometrics** are powerful emerging modalities and are becoming a promising technology for automatic and accurate individual recognition in human identification, including electrocardiograms (ECGs) (Zhang et al.,) and electroencephalograms (EEGs) (Kumari and Vaish, 2015). For example, Martinovic, et al. proposed a pulse-response biometric system to enhance the security of continuous authentication on a secure terminal (Martinovic et al., 2017). More specifically, Barra, et al. proposed a physiological biometric system based on the extraction of fiducial features (peaks) from the ECG combined with the spectrum features of the EEG to support better authentication in healthcare applications (Barra et al., 2017).
3. **Multimodal Biometrics** have been proposed to combine physiological and behavioral biometrics to improve the robustness (Bansal et al., 2017). In (Gowda et al., 2017), Gowda, et al. developed a hybrid biometric system in which both psychological and behavioral traits are fused at the score level, including face, palm, signature and

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speech traits. Furthermore, Sultana, et al. proposed mining social behavioral information from an online social network and fused traditional face and ear biometrics to enhance the performance of a traditional biometric system (Sultana et al., 2017).

Obviously, physiological biometrics are suitable for authentication in healthcare systems because the complexity and scalability that behavioral and multimodal biometrics often need to collect more data are unconnected with user healthcare. Therefore, ECG-based biometrics are widely used to provide continuous authentication for healthcare systems (Satija et al., 2017; Zebboudj et al., 2017; Zaghouani et al., 2017).

However, based on a comprehensive investigation of ECG-based authentication, in (Fratini et al., 2015), A. Fratini et al. concluded that that new techniques will be developed to improve the authentication accuracy, especially for scenarios that include a large number of users. Hence, this paper proposes a parallel ECG-based authentication named PEA for smart healthcare systems to provide more accurate and effective biometrics. Specifically, the main contributions of this work include the following:

- Addressing the instable accuracy of authentication in different scenarios, this paper proposes a hybrid ECG features extraction integrating fiducial and non-fiducial based features. This approach attempts to extract more comprehensive ECG features to improve the authentication stability.
- To improve efficiency, this paper proposes parallel ECG pattern recognition based on MapReduce that can effectively search the multimodal ECG feature space.

The remainder of this article is organized as follows. Section 2 presents the detailed design of the proposed scheme. Section 3 describes the proposed hybrid ECG feature extraction consisting of fiducial and non-fiducial features. The proposed parallel ECG pattern recognition is introduced in Section 4, followed by the experimental analysis in Section 5. Finally, Section 6 concludes this paper.

2. System design

2.1. Motivation and design issues

The proposed ECG-based authentication is considered to be highly promising in terms of user identification for smart healthcare systems because of its attractive features:

- **Inimitability**: Many significant works have proved that ECG is an inherent vital signal that cannot be easily imitated, unlike fingerprints, voice, iris and other biometrics (Arteaga-Falconi et al., 2016).
- **Suitability**: ECG is more crucial than other physiological signals that some biometrics are not available for those who are visually impaired and have amputations (Sidek et al., 2014).
- **Accessibility**: Because smart healthcare systems often need to collect various physiological data, among which ECG is one of the most important vital signals to monitor, ECG is convenient for authentication.
- **Comfortability**: Compared with other physiological biometrics, especially EEG, ECG data are easily collected from comfortable conventional mobile or wearable devices (Kang et al., 2016).

2.2. Framework of PEA

Addressing these design issues, this paper proposes PEA to provide a more suitable authentication process for smart healthcare systems. In Fig. 2, the framework of PEA is illustrated and includes the following components:

- **Physiological Data Collection**: Physiological information is collected through telemedical terminals, wearable devices, sensors, etc. Only ECG signals are transmitted to the authentication server, and other physiological data are not transmitted to the healthcare data center until the user is identified.
- **Hybrid ECG Feature Extraction**: In PEA, fiducial- and non-fiducial-based features are extracted for ECG pattern recognition. In particular, non-fiducial-based features include morphological and spectral features.
- **Parallel ECG Pattern Recognition**: Assisted by cloud computing, Big Data and other techniques, parallel ECG-based identification is available and efficiently supports authentication. Specifically, linear discriminant analysis (LDA) and 2-dimensional principal component analysis (2DPCA) are implemented in PEA to improve the authentication accuracy because their effectiveness in ECG pattern recognition has already been widely proved (Varatharajan et al., 2017; Huang and Zhang, 2014; Xie et al., 2016; Pinto et al.,).
- **Physiological Data Transmission**: After authentication, all the sensed physiological data are transmitted to the healthcare data center.

2.3. Scenarios

Due to the privacy of healthcare data, authentication has attracted more attention in the development of telemedicine and healthcare systems. Through PEA, only an ECG signal is used to provide acceptable authentication. Because ECG signals are monitored in nearly all telemedicine and healthcare systems, PEA could be implemented in the following representative scenarios:

- In an emergency, a patient may be unable to provide details about their medical history, allergies, etc., which are critical and helpful for emergency treatment. Assisted by PEA, the system can identify the patient, whose hospital information can then be accessed.
- Currently, although wearable devices are widely used, most only support conventional authentication methods, e.g., logging in with user name and password. However, it is often not convenient to enter account details while exercising. Through PEA, as long as an ECG signal can be sensed, rapid and continuous authentication would be available.

3. Hybrid ECG feature extraction

To accurately represent ECG features, as much information as possible should be involved in feature extraction. Therefore, this paper proposes a hybrid ECG feature extraction technique that includes fiducial- and non-fiducial-based features.

3.1. Fiducial based feature extraction

It has been widely accepted that PQRST-peaks are the most significant fiducial-based features of ECG; they are marked and stored over the entire ECG signal, and the peak is specified as R-peak (Ravanshad et al., 2014). Thus, PQRST-peaks are considered the main fiducial features in the proposed scheme.

Fig. 1 illustrates a typical ECG signal waveform, where PQRST-peaks can be determined by wavelet transform (Banerjee and Mitra, 2014). Specifically, PQ, QR, RS and ST duration scans can be directly calculated to represent the time-domain features of the ECG signal. Furthermore, the R-peak has a minimal impact on ECG recognition, and only the amplitudes of PQ, PT and SQ are calculated to represent the amplitude features of the ECG signal. In summary, the time-domain and amplitude features can be extracted through a PQRST-peak-based approach.

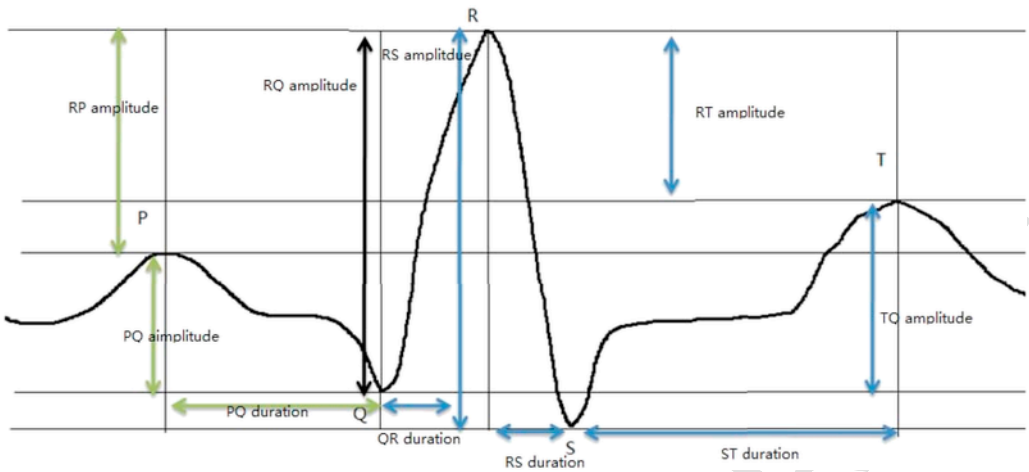

Fig. 1. PQRST-peaks feature extraction from the ECG signal.

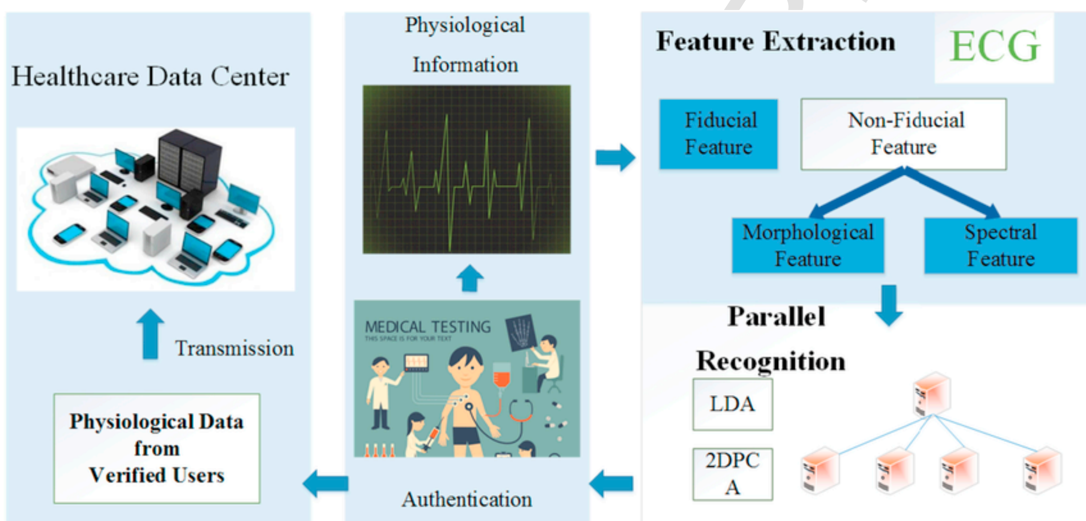

Fig. 2. Framework of PEA

3.2. *Non-fiducial-based feature extraction*

3.2.1. *Morphological features*

Morphology features, which are one of the most representative ECG non-fiducia- based features, are easily recognized. Hence, the proposed scheme includes morphological features in the hybrid ECG feature extraction. Specifically, the morphological features are extracted with the following steps:

1. The ECG signal matrix of User i is established through Equation (1), where C represents the number of the ECG signal files of this user, N represents the number of signal periods in each ECG file, and S_j is the ECG signal value acquired at timestamp j.

$$\begin{cases} X_i = \bar{x}_1, \bar{x}_2, \ldots, \bar{x}_C \\ \bar{x}_C = \frac{1}{N}\sum_{j=1}^{N} S_j \end{cases} \tag{1}$$

2. The global hash matrix is generated through Equation (2), where P represents the number of users.

$$G = \frac{1}{P*C}\sum_{i=1}^{P*C}\left(X_i - \frac{\sum_{i=1}^{P*C} X_i}{P*C}\right)^T \left(X_i - \frac{\sum_{i=1}^{P*C} X_i}{P*C}\right) \tag{2}$$

3. Then, the eigenvalues and eigenvectors of G can be directly calculated. According to their physical significance, the top-n eigenvalues and corresponding eigenvectors can approximately represent the original matrix; i.e., they are considered the morphological feature.

3.2.2. *Spectral features*

Generally, the spectral features of ECG signals are robust and are not affected by the environment. Although they are difficult to distinguish, these features can be involved in the proposed exaction to improve the robustness. Specifically, ECG spectral features can be extracted through the following steps:

1. ECG signal of User i is normalized to be *signal*(i).
2. The linear prediction coefficients (LPCs) of *signal*(i) are calculated through Equation (3), where a_i is determined by the minimum error method. Specifically, the minimum error $e[n]$ can be calculated by

Levinson-Durbin (Zeinali and Shafiee, 2016), as presented in Equation (4).

$$p(n) = -\sum_{i=1}^{P} a_i * signal(i+1) \tag{3}$$

$$e(n) = p[n] - signal(n) \tag{4}$$

3. The spectrum of $p[n]$, i.e., $Z(\Omega)$, can be generated by the Fast Fourier Transformation (FFT), as shown in Equation (5); then, the feature of the ECG signal can be quantitatively analyzed.

$$\begin{cases} Z(\Omega) = \int p(t)\exp(-j\Omega t)\,dt \\ p(t) = \frac{1}{2\pi}\int Z(\Omega)\exp(j\Omega t)\,dt, \Omega = 2\pi t \end{cases} \tag{5}$$

4. Parallel ECG pattern recognition

4.1. Theory model

Parallel processing is the key technique that support incremental training, in which only new data must be trained rather than re-training all of the data when new data are generated. Fig. 3 illustrates the detailed theory model of the proposed algorithm.

1. Assisted by the distributed infrastructure of MapReduce, the raw data are divided into multiple subsets, *Sample*1, …, *SampleN*, for training and recognition.
2. Each subset representing the hybrid features of the ECG signal is partitioned into multiple blocks.
3. Through linear discriminant analysis (LDA), the hybrid features can be extracted and four feature spaces calculated: the amplitude space *A*, the duration space *D*, the spectrum space *S* and the morphology space *M.* Note that it has been proved that though LDA can achieve good performance, an approach that integrates LDA and two-dimensional principal component analysis (2DPCA) can significantly improve the accuracy, as presented in Section 5.
4. Finally, the optimal result can be obtained by traversing the hybrid feature spaces.

4.2. Algorithm design and implementation

In contrast to the traditional pattern recognition algorithms, the proposed approach includes two search processes: searching in the same feature space and in different feature spaces. Based on the model described in Subsection 4.1, the proposed parallel algorithm efficiently improves the authentication accuracy, and both the quick search and the incremental model are supported. Fig. 4 illustrates the proposed parallel search scheme, in which a suitable result similar to the input pattern ‘Test’ is found by the following steps:

1. First, the features should be extracted from ‘Test’; however, the proposed algorithm is different in that ‘Test’ is transmitted to each node and there is a private abbreviated feature space named ‘Feature Space Split.’
2. Then, the ’Test’ features are extracted. The number of features is *r*, which corresponds to the number of ’Feature Space Split.’ Note that only one feature is extracted by the conventional approach.
3. Through a two-round search, an optimal value is found according to the occurrence probability in multimodal feature spaces.

Furthermore, Fig. 5 shows the details of the proposed two-round search in multimodal feature space.

1. The first-round search is expected to find the local optima in each feature space, i.e., *l_Result*1, …, *r_Result*4. Specifically, ‘Test’ must be projected with each ‘Subspace’ in each ‘Space’, and each ‘Space’ incudes four ‘Subspaces’, i.e., Subspaces A, D, S and Z.
2. In the second-round search, the resulting sets from all the ‘Subspaces’ are merged as < *Result, frequency* > , representing the probability of each result in the overall feature space. Then, the global optimum can be deduced.

5. Experiment

5.1. Experimental dataset and environment

To verify the performance of the proposed scheme, the MIT-BH database[1] is considered the main experimental dataset. Specifically, MIT-BH includes 100 samples, and each sample contains 200 ECG signal files; thus, this dataset includes 20, 000 ECG signals. Moreover, 100 morbid samples are added to the experimental dataset by considering the diversity of the data sources. Each sample includes 10, 000 signals that are equal to the volume of the ECG signal of one user that is acquired in approximately 10s.

The experimental environment is constructed by four computers with a computer with a Intel (R) Xeon (R) i7 CPU, 32 core thread 16, 128 GB memory, and 16 TB drive. Moreover, the operating system is Ubuntu 12.04, and the version of Hadoop is 0.23.11.

5.2. Experimental results

Three experiments are designed to evaluate the performance of the proposed scheme in terms of recognition, classification and efficiency.

5.2.1. Comparison between different features

As mentioned before, the proposed scheme involves four categories of ECG features: time-domain and amplitude features by PQRST-peaks, spectral features from FTT, and morphological features. These features are extracted through three approaches, i.e., PQRST, FTT and morphology, so an experiment is designed to compare the recognition accuracy between PQRST, FTT, morphology and the proposed hybrid feature-based approach. This experiment contains 20, 000 samples, and a random ECG signal is selected from each sample to verify whether it is successfully recognized as the source sample.

Fig. 6 shows that although the fiducial- and non-fiducial-based feature extractions are widely implemented in ECG recognition, the accuracy of these approaches is not very good. In particular, the accuracy of PQRST- and FFT-based approaches ranges from only 70%–75%, respectively.

Although the accuracy of the morphology-based approach surpasses 91%, it is essentially a typical implementation of pattern recognition. Moreover, ECG morphology represents multimodal ECG features, so it could be considered a simple hybrid ECG feature extraction.

The proposed hybrid feature-based approach demonstrates considerable performance, as its accuracy surpasses 99%. Only 3 morbid ECG signals are not recognized accurately, which means that the interference of the proposed scheme should be further improved. However, the

[1] http://ecg.mit.edu/.

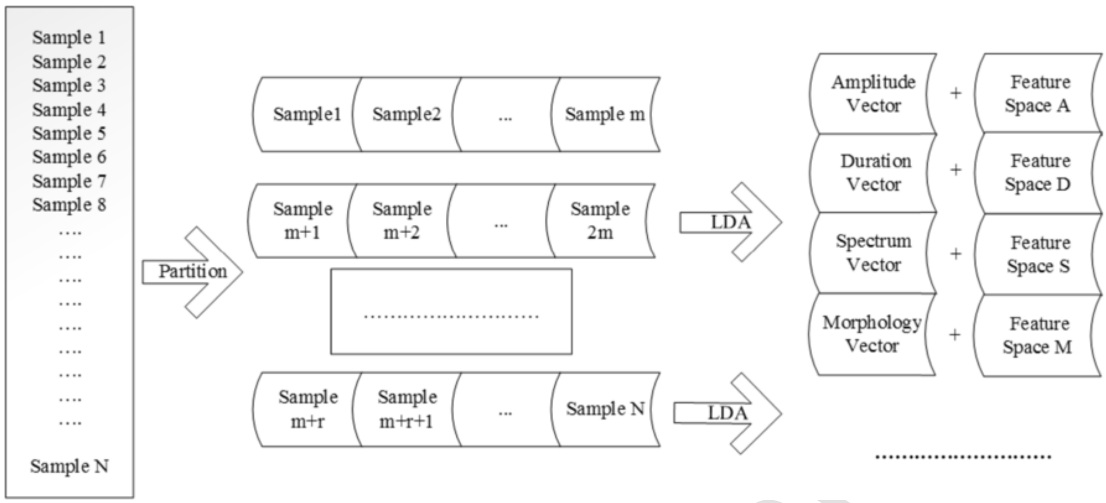

Fig. 3. Theory model of the parallel ECG pattern recognition algorithm.

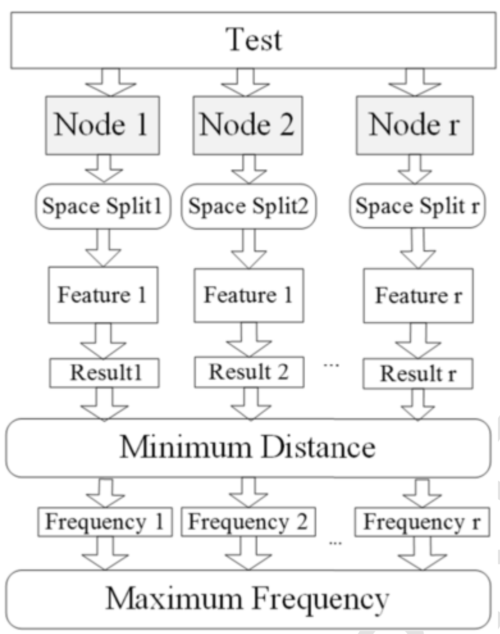

Fig. 4. Parallel search scheme.

presence of more features that involve ECG recognition will inevitably lead to increased computation loads. Thus, a distributed or parallel computing framework should be implemented to improve the efficiency.

5.2.2. Evaluation of ECG recognition

The accuracy of ECG recognition is the key indicator of biometric-based authentication. Thus, the proposed scheme is evaluated through the Mahalanobis distance. Specifically, a random ECG signal is selected from a sample, and the experimental data include 100 samples. Then, the Mahalanobis distance is measured after recognition to evaluate the accuracy; i.e., a lower Mahalanobis distance represents a higher recognition accuracy.

In the proposed algorithm, 2DPCA is implemented to improve the performance, which can theoretically maintain the vital features while removing the redundancy factors. Thus, this experiment is expected to evaluate the availability of the proposed algorithm and compare it with the conventional LDA-based approach.

In Fig. 7, the comparison between the proposed pattern recognition and LDA-based approach is shown. It is obvious that the accuracy of the proposed scheme is higher than that of the LDA-based approach when evaluating the No. 0 and 65 samples, but the overall performance of these two approaches does not demonstrate significant differences. In summary, the accuracy of the proposed scheme is considerable and stable; it effectively avoids the small sample size problem that is often found in LDA-based approaches.

5.2.3. Evaluation of the parallel algorithm

Through the above experiments, the availability of the proposed scheme has been verified. However, the results also prove that the proposed hybrid feature-based approach needs more computing resources, which would decrease the efficiency of authentication, especially for scenarios that involve a large number of users.

Based on the parallel scheme shown in Fig. 4, 100 user ECG signal files are processed by 4 'Nodes' in this experiment. In particular, each 'Node' has 8 feature subspaces.

Table 1 illustrates the processing at Node 1. Specifically, in the PQRST feature space, the recognition result of subspace 1 is '1', and the corresponding Mahalanobis distance is '1711.58'. The rest of the subspace may be inferred. In particular, because the recognition result of subspace 3 is '16' and the corresponding Mahalanobis distance is '0.00', the local optima is in the PQRST feature space. In the same way, the local optima in FFT feature space is '16', while it is '16' in morphology. Finally, because the local optima in each feature space is '16', it is extremely possible that the global optimum of Node 1 is '16', i.e., that this signal is recognized as the 16th user.

5.3. Discussion

Although the experimental results verify that the proposed scheme provides a suitable authentication method for smart healthcare systems, the following limitations should be addressed in practical implementation:

- **Scalability**: In the proposed approach, the hybrid ECG features include fiducial, morphological and spectral features. With the development of telemedicine and e-healthcare, it is a great challenge to involve more features to achieve better biometrics.
- **High Throughput**: Due to the limited experimental dataset, the ability of the proposed approach could not be evaluated to harness high-throughput data in practical scenarios, such as tertiary hospitals.

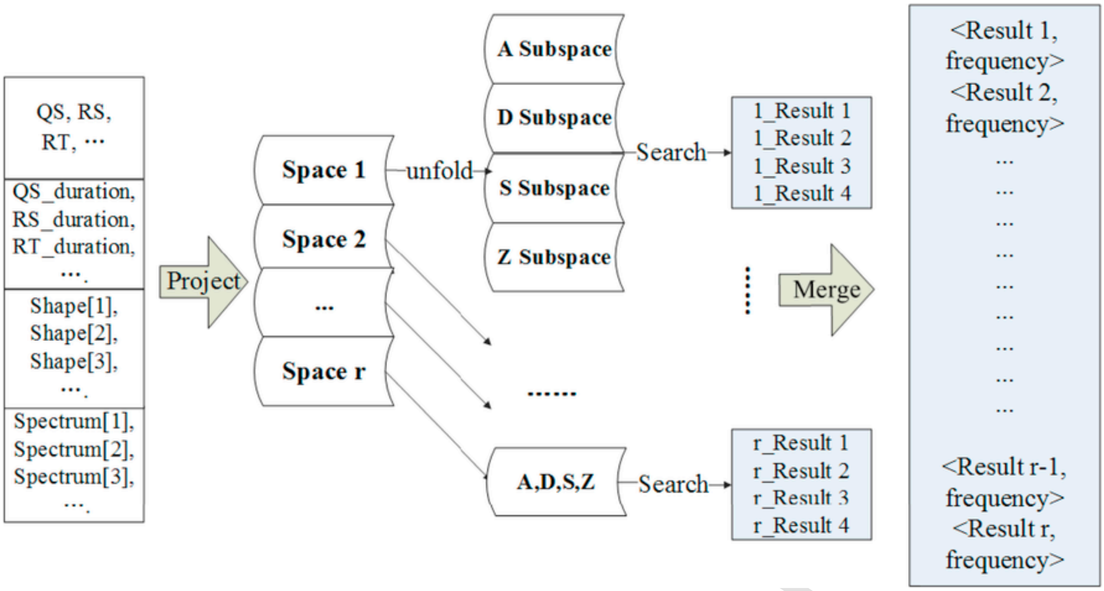

Fig. 5. Two-round search in multimodal feature space.

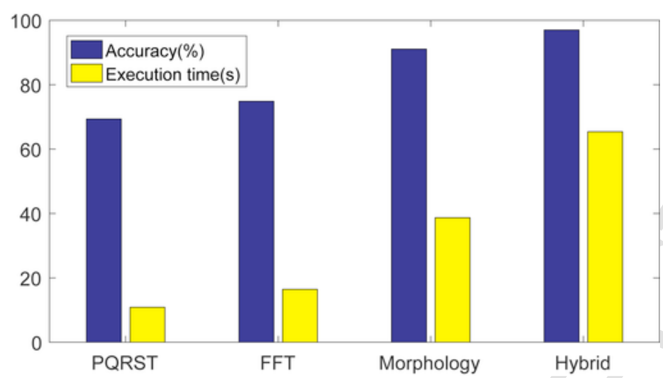

Fig. 6. Comparison of four ECG features.

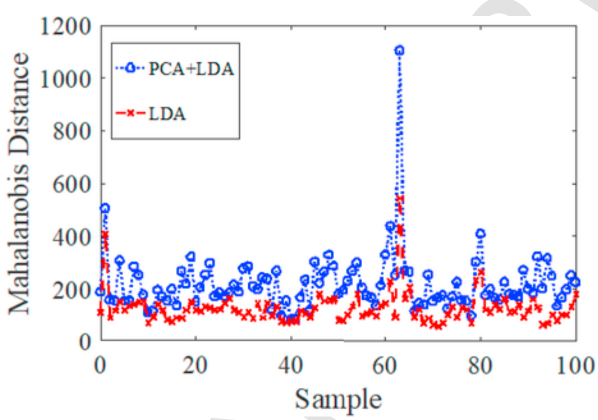

Fig. 7. Comparison between the proposed pattern recognition and LDA-based approaches.

6. Conclusions

To improve the accuracy and efficiency of ECG-based authentication, this paper proposed a parallel approach that incorporates multiple features for smart healthcare systems. Specifically, fiducial- and non-fiducial-based features, i.e., PQRST, spectral and morphological features, are comprehensively considered for ECG recognition. Assisted by a parallel computing framework, the recognition is divided into the following two processing methods: searching local optima in each feature space and searching global optima. Through adequate experiments, the performance of the proposed scheme is verified, and the results indicate that the accuracy and efficiency are considerable compared with those of other conventional approaches.

However, the experimental results also illustrate that the proposed authentication is susceptible to the effects of cardiac disease. Therefore, our future work will focus on improving the robustness of the ECG-based authentication for cardiac patients.

Table 1
Processing at node 1.

	PQRST		FTT		Morphology	
	Recognition Result	Mahalanobis Distance	Recognition Result	Mahalanobis Distance	Recognition Result	Mahalanobis Distance
Subspace 1	1	1711.58	1	15.52	1	500.51
Subspace 2	7	1931.19	9	75.89	8	330.23
Subspace 3	**16**	**0.00**	**16**	**0.00**	**16**	**184.83**
Subspace 4	24	908.71	19	19.21	19	244.57
Subspace 5	43	1351.42	34	33.26	42	471.96
Subspace 6	54	1380.87	53	19.54	53	267.18
Subspace 7	63	1617.44	71	31.42	72	362.31
Subspace 8	85	2173.29	85	38.17	83	380.38

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