



# An integration of features for person identification based on the PQRST fragments of ECG signals

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## Abstract

In this document, the aim of this study is to identify the subjects using PQRST fragments of the electrocardiogram (ECG) signal. The ECG signal is an emerging technology for person identification. Our identification system has three principal steps, namely preprocessing, features extraction, and classification. In the first step, the filtering technique is used to remove the noise of the ECG signal. After filtering, the algorithm of T peaks detection is implemented for realizing the segmentation. (This work focuses on the PQRST fragments.) In the second step, a combination of the features such as cepstral coefficients, entropy, and zero crossing rate is proposed in this work. After feature extraction step, the machine learning model like the support vector machines is used for the classification step. A combination of the different features is evaluated using two public databases such as ECG-ID database and Massachusetts Institute of Technology–Boston’s Beth Israel Hospital Arrhythmia DataBase obtained from the Physionet database. Our proposed system gives an accuracy rate of 92.5% with ECG-ID database (all-recordings) and 98.6% with MIT–BIHA database.

**Keywords** Person identification · Electrocardiogram signal · PQRST fragment · Preprocessing signal · Features extraction · Machine learning

## 1 Introduction

The biometric is the person recognition based on the behavioral or physiological characteristics such as face, fingerprint, voice, iris, ear, gait, retina, vein, etc. [1–3].

Biometrics identifies the actual individuals than other traditional methods like passwords, etc. [4–6]. Though these methods are not robust, the private biometric information are not secured. In the last years, the researchers have used ECG signal as a biometric measures to identify the persons [7–9]. In fact, the ECG is not only used for diagnosis, but it is also used for biometric [10]. Due to the unique characteristic of ECG, it is more difficult to imitate [11]. Each ECG signal is composed of P wave, QRS complex, and T wave. An ECG is a test that records the electrical activity of the heart [12]. The recognition of individuals by ECG signal is a very interesting subject [13]. Recently, ECG signal is used in various

biometric applications [13]; we can cite the military, the bank, the video game market and online platforms, etc. [14–23].

The initial hypothesis of this work is to identify the person using the PQRST fragments for each ECG signal of the person. To obtain this hypothesis, it is necessary to apply three main steps such as preprocessing, features extraction, and classification. The novelty of this study is that we proposed to use a new sources of information extracted from each PQRST fragment.

The main purpose of this paper is to give a better accuracy rate for human identification system. For that, the combination of different features (such as 12 cepstral coefficients, entropy, and ZCR) is used in this study. In addition, the linear-SVM, the radial basis function (RBF)-SVM, and the polynomial-SVM are applied for the classification. The ECG-ID database and the MIT–BIH Arrhythmia database are used in this research to evaluate our identification system.

The remainder of this paper is structured as follows. In Sect. 2, a literature review of the previous work is presented. In Sect. 3, the materials and methods are explained. In Sect. 4, the experimental results and discussion are described. Finally, Sect. 5 is the summary of the whole manuscript.

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## 2 Related work

In recent years, several studies have worked on the identification of individuals by ECG signals using different methods for feature extraction as well as methods for the classification of persons.

Dar et al. [24] proposed a combination of discrete wavelet transform (DWT) and heart rate variability (HRV) for the extraction of characteristics, and for the classification used random forests (RF). The proposed system is evaluated on three benchmark databases, namely MIT–BIH Arrhythmia, MIT–BIH Normal Sinus Rhythm (NSR), and ECG-ID database including all subjects. Then, they obtained an accuracy rate equal to 95.85% of the MIT–BIH Arrhythmia database, 100% of the NSR database, and 83.88% of the ECG-ID database.

Sarker et al. [25] used the fiducial features for the extraction of characteristics, and applied linear discriminant analysis (LDA) and  $K$ -nearest neighbors (KNN) for classification. The method which has been proposed gives an accuracy rate equal to 95% using the MIT–BIH Arrhythmia database.

Dar et al. [26] introduced a Haar Transform method for features extraction and applied the KNN method for classification. The proposed method achieved an identification rate of 83.2% using the ECG-ID database. In 2017, Zhang et al. [27] introduced a DWT and multiresolution 1D convolutional neural network (1D-CNN). Then, the softmax method is used for classification and which achieve accuracy equal to 91.1% using the MIT–BIH Arrhythmia database.

In 2019, Alhan et al. [28] applied logarithmic grid analysis on the second-order difference plot (SODP) features which has achieved classification rates with KNN of 91.96%, 98.46%, and 99.86% for ECG-ID, MIT–BIH Arrhythmia, and NSR.

Di Wang et al. [29] presented a feature extraction method such as DWT based on softmax method for classification. The proposed system was tested on a MIT–BIH database of 36 person which achieved accuracy rate equal to 96.82%.

## 3 Materials and methods

The proposed system consists mainly of the different parts: (1) preprocessing; (2) T peaks detection; (3) segmentation; (4) features extraction; and (5) classification. Figure 1 represents the diagram of our ECG identification system proposed in this study.

### 3.1 Databases

In this research, the ECG-ID database and the MIT–BIH Arrhythmia database were selected to evaluate our proposed identification system.

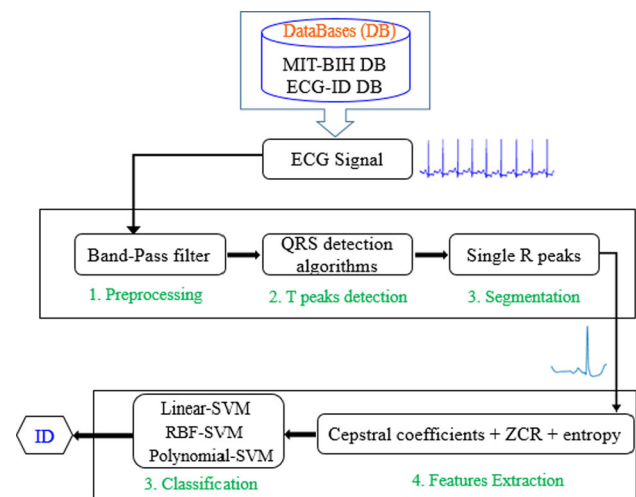


Fig. 1 Architecture of our proposed system

The MIT–BIH Arrhythmia<sup>1</sup> database contains 48 recordings from 47 persons (25 males and 22 females). In fact, there is a person have two ECG records.

In the ECG-ID<sup>1</sup> database consists of 310 recordings collected from 90 persons (44 males and 46 females) who have one to twenty recordings. During the experiments, all ECG recordings of this database were used.

In this experiment, for each selected subject, the training dataset was constructed using 70% of the ECG recordings, while test dataset was built using 30% of the ECG recordings.

### 3.2 Preprocessing

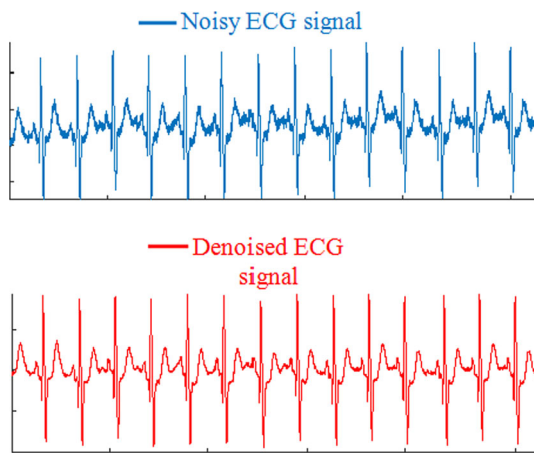
The preprocessing technique is an important stage before the features extraction stage to improve the performance of the system. The ECG signals which are touched by noise like power noise, baseline wander, and high-frequency noise are prepared utilizing a filtering method [27,30]. The band-pass filter with cut-off frequencies at 2 Hz and 50 Hz is chosen in this work. Figure 2 shows an example of ECG signal which contains noises and after filtering.

### 3.3 T peaks detection

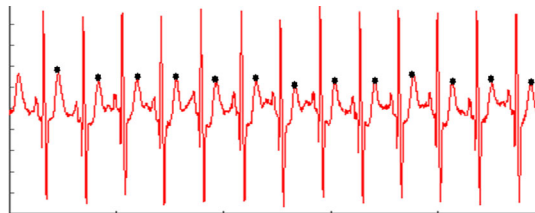
In our study, the T peaks detection is necessary for the segmentation step. The QRS detection algorithm is used in this paper to detect the all of the T peaks [31]. The location (position: instant and amplitude) of T peaks detection for each ECG signal is determined by this algorithm [31].

Figure 3 shows the result of the T peaks detection.

<sup>1</sup> <https://archive.physionet.org/cgi-bin/atm/ATM>.



**Fig. 2** Example of ECG signal with noises and ECG after filtering



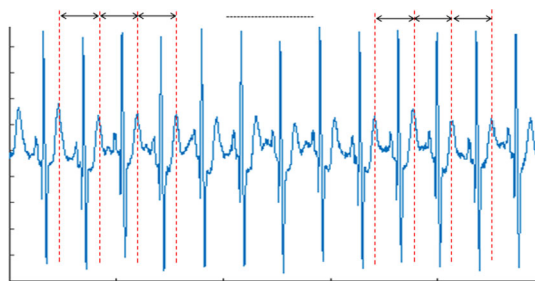
**Fig. 3** Detection of T peaks

### 3.4 Segmentation of the ECG signal

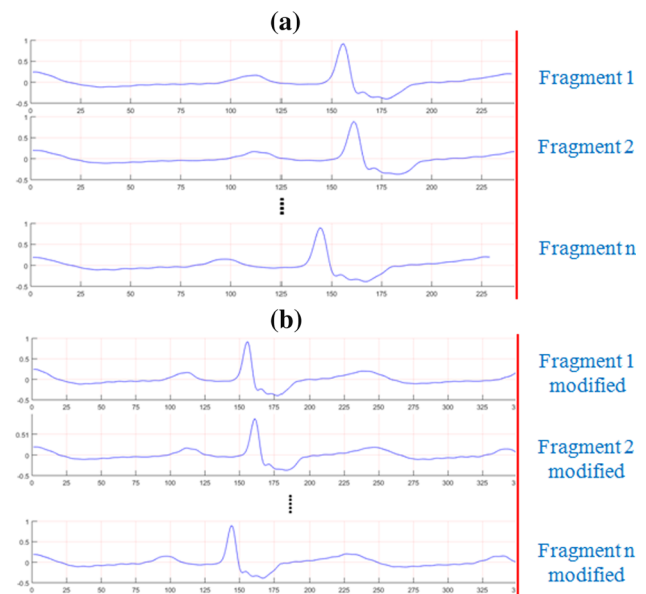
The segmentation is an important step before the features extraction step. After the detection of T peaks, the segmentation stage is realized. In this step, we segmented each ECG signal into several PQRST fragments. In each fragment, we have only one R peak (see Fig. 4).

After the segmentation step, the normalization is applied in this work. The reason to apply the normalization after the segmentation step is that the PQRST fragments are not of the same size [32].

Figure 5 illustrates the results after the normalization.



**Fig. 4** Segmentation of the ECG signal with single R peak (R)



**Fig. 5** Normalization: **a** before and **b** after

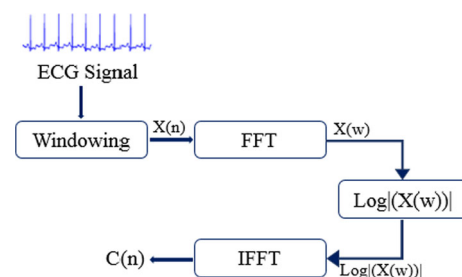
## 3.5 Feature extraction

In our research, before the classification step, the feature extraction such as the fusion of diverse parameters is used. The parameters used in this document are cepstral coefficients, entropy, and ZCR. These parameters are widely used in the field of speech recognition [33–36]. A combination of the parameters is proposed in this work for an increase in the performance of the system.

### 3.5.1 Cepstral coefficients

The cepstral coefficients are then given by the inverse fast Fourier transform applied (IFFT) to the logarithm of the fast Fourier transform modulus (FFT) of the ECG signal [34].

Figure 6 presents the necessary steps to calculate the cepstral coefficients.



**Fig. 6** Steps of the cepstral coefficients

### 3.5.2 Entropy

The parameter of the entropy makes it possible to measure the average information provided by the knowledge of  $x$ . For a source which is a random variable with  $n$  values, each value  $x_i$  having a probability  $P(x_i)$  of appearing [37]. The entropy  $H$  of the source  $x$  is defined as:

$$H(x) = - \sum_i P(x_i) \log_2[P(x_i)] \quad (1)$$

### 3.5.3 ZCR

The zero crossing rate (ZCR) represents the number of times the signal, in its amplitude/time representation, passes through the zero value [38,39].

It is defined by the following equation:

$$\text{ZCR} = \frac{1}{N-1} \sum_{n=1}^{N-1} \text{sign}(s(n)s(n-1)) \quad (2)$$

### 3.5.4 Fusion of the features

In our work, the combination of diverse features (12 cepstral coefficients, entropy, and ZCR) is used. These features are integrated in one vector (i.e., each fragment of the ECG signal has one vector). Our proposal is to combine the parameters into a single vector to increase the performance of the system. Figure 7 and Table 1 present the integration of the features into a single vector.

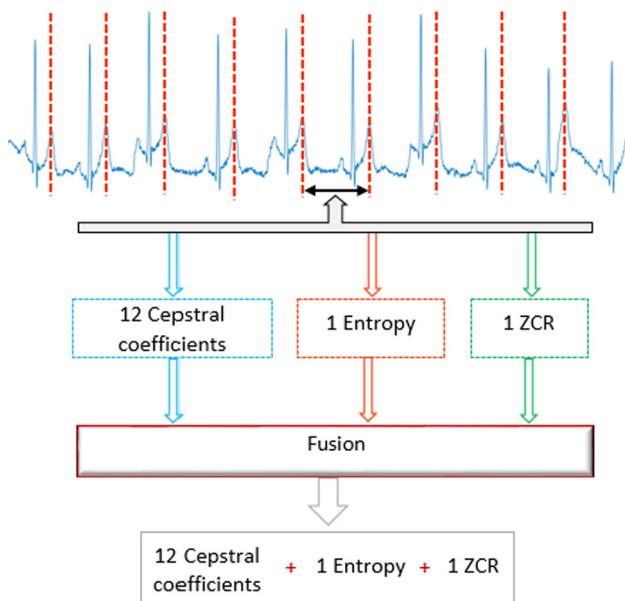


Fig. 7 Integration of the features

**Table 1** Different feature extractions

Features extraction
12 Cepstral coefficients
1 Entropy
1 ZCR

### 3.6 The classifier identification

– SVM (Support Vector Machine)

Support vector machine (SVM) was developed by Vapnik in 1995 as a discriminatory classification tool for the classification [40]. The principle of SVM is simple: its aim is to separate the data into classes using a border as simple as possible, in such a way that the distance between the different groups of data and the border which separates them is maximum [41]. This distance is also called margin, and SVMs are thus referred to as wide margin separators, the support vectors being the data closest to the border [41]. This notion of border assumes that the data are linearly separable, which is rarely the case. To overcome this, SVMs often rely on the use of kernels. These mathematical functions allow separating data by projecting them in a feature space.

In this study, three types of kernel functions are used such as linear, RBF, and polynomial.

**Linear:**  $k(x_i, x_j) = x_i^T x_j$

**RBF:**  $k(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \gamma > 0$

**Polynomial:**  $k(x_i, x_j) = (\gamma x_i^T x_j + r)^d, \gamma > 0$

The  $\gamma$ ,  $d$ , and  $r$  parameters are, respectively, the kernel flexibility control, the degree of polynomial, and the weighting parameter.

**Table 2** Best accuracy obtained the ECG-ID DB with SVM kernel function

Database	Features extraction [Cepstral coefficients+entropy+ZCR]		
	Linear-SVM	Polynomial-SVM	RBF-SVM
ECG-ID	86.7%	79.2%	<b>92.5%</b>

Bold value indicate the best result obtained with RBF kernel function with an accuracy equal to 92.5%

**Table 3** Best accuracy obtained the MIT-BIHA DB with SVM kernel function

Database	Features extraction [Cepstral coefficients+entropy+ZCR]		
	Linear-SVM	Polynomial-SVM	RBF-SVM
MIT-BIHA	<b>98.6%</b>	92.9%	96.5%

Bold value indicate the best result obtained with Linear kernel function with an accuracy equal to 98.6%

**Table 4** Performance comparison with similar works

Authors	Features	Classifier	Database	Accuracy (%)
Dar et al. [26]	Haar Transform	KNN	MIT-BIH (47 subjects)	95.9
			ECG-ID (90 subjects)	83.2
Dar et al. [24]	Haar Transform and HRV	Random Forest	MIT-BIH (47 subjects)	93.1
			ECG-ID (90 subjects)	83.9
Di Wang et al. [29]	DWT + Sparse Autoencoder (S-AE)	Softmax	MIT-BIH (47 subjects)	96.82
			ECG-ID (90 subjects) (all recording)	92.3
Sahin et al. [45]	Proposed polynomial curve fitting based ECG features	SVM	MIT-BIH (36 subjects)	95.46
Proposed approach	12 cepstral coefficients + entropy + ZCR	Linear-SVM Polynomial-SVM RBF-SVM	MIT-BIH (47 subjects)	98.6
			ECG-ID (90 subjects) (all recording)	92.5

The adjustment of these parameters is done empirically. SVM classifier is used widely for signal processing [42–44].

## 4 Experimental results and discussion

We have described in the previous sections: (1) the method which we proposed in this study is the combination of the characteristics, namely the 12 cepstral coefficients, the entropy parameter, and the ZCR parameter, (2) as well as the classification method here we applied three most used kernel functions, namely linear-SVM, polynomial-SVM, and RBF-SVM, (3) also the databases which we used to evaluate our work, in this paper, we used two public databases such as ECG-ID DB and MIT-BIHA DB.

In this experiment, for each selected subject, the training dataset was constructed using 70% of the ECG recordings, and for the test dataset was constructed using 30% of the ECG recordings.

For the ECG-ID database, we first applied the linear kernel function of SVMs. Next, we start to vary the regularization parameter  $c$  of this kernel function in order to find the best identification rate (accuracy rate). In this work, we obtained the best result with the value of  $c$  equal to 10,000 with an accuracy rate equal to 86.7%. Second, we applied the polynomial kernel function of SVMs. This kernel function has four important parameters such as the parameters  $c$ ,  $\gamma$ ,  $r$ , and  $d$ . We have done the variation of each parameter of the polynomial kernel function and the best rate found when these parameters are, respectively, equal to 100,000, 0.05, 0.005,

and 3 with an accuracy rate equal to 79.2%. In addition, with the kernel function RBF, we varied its parameters  $c$  and  $\gamma$ . These parameters give a better result that is equal to 92.5% when the parameter  $c$  equal to 10,000 and the parameter  $\gamma$  equal to 0.00055.

Table 2 represents a summary of the best accuracy obtained by the ECG-ID DB using a fusion of three methods of features (cepstral coefficients, entropy, and ZCR) with linear-SVM, polynomial-SVM, and RBF-SVM.

We apply the same work for the MIT-BIHA database (see Table 3).

In this study, a combination of the methods such as 12 cepstral coefficients, the entropy, and ZCR for human identification was developed. The ECG signals were filtered with band-pass filter and segmented into heartbeats by taking the detected T peaks (i.e., in each segment has one R peak) using the QRS detection algorithm. After the normalization of the segments (make the same size), on each given segment, we extracted the following parameters: 12 cepstral coefficients, entropy, and ZCR. Then, we combine these features in one vector. In our work, we first tested with only 12 cepstral coefficients, and only with entropy, then with ZCR alone. Next, we have combined two by two. After that we have combined the three methods. In addition, SVM was implemented in this work to do the classification of the person. We tested with linear, polynomial, and RBF kernel functions of the SVM. Indeed the combination of all the characteristics gives a good identification. Our methods are mostly used in the field of recognition such as the speech recognition and give a good identification rate.



The limitation of this work is the unbalanced number of samples for each subject; for that we propose to use the data augmentation in the next work. We compare our work with others like [24,26,29,45]. The table below represents a comparison with similar studies (Table 4).

## 5 Conclusions

In this paper, we propose a combination of the methods for human identification. In this study, the parameter extraction methodology extracts the characteristics of each segment after detection of T peaks. The proposed work concentrates mainly on combination of features that contain both acoustic characteristics (such as 12 cepstral coefficients and ZCR) and prosodic characteristics (such as entropy) of each segment in ECG signal. The performance of the proposed method is examined by SVM for person recognition. For evaluation, we used 90 individuals from ECG-ID database and 47 individuals are taken from MIT-BIH Arrhythmia database. Finally, our proposed system shows 98.6% accuracy for MIT-BIH DB and 92.5% for ECG-ID DB.

In future, we can think about using deep learning for improving the identification rates.

## Declarations

**Conflict of interest** The authors declare no conflict of interest.

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