

# A New ECG-based Identification System using Morphology Scaling and Statistical Parameters

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## Abstract

The uniqueness of electrocardiographic (ECG) signals and robustness against copying or forgery has led to use them for constructing ECG-based identification algorithms. However, one of the challenges in the design of ECG based identification algorithms is the feature extraction from these signals. This procedure typically is performed by techniques based on conversion or waveform (i.e. morphology). Diagnosis and determination of parameters of morphology techniques are troublesome tasks and there would be high possibility of deficiencies and error while using morphology parameters. In addition, due to the changes in these parameters in different cycles of heart rate, relative similarities between these parameters from different people may be established, which would reduce the performance of morphological characters for identification purpose. Therefore, a new algorithm based on statistical parameters of the signal and parameters scaling is proposed to overcome the mentioned problems in this study. Performance of the proposed method is evaluated in a statistical community including 20 to 69 people, with population growth step of 5%. Results show that in all cases, the whole community is identified with 100% accuracy. This shows that compared with the morphological parameters method, the proposed algorithm improves the accuracy from 5% up to 22/64%. This shows that the proposed approach has better performance especially in large statistical communities.

## Keywords:

*Electrocardiogram (ECG); Identification; Morphology scaling; Statistical parameter*

## 1. Introduction

Nowadays, with the development of society as well as the growing trend of technology, the use of traditional methods for identity detection, such as keystrokes, passwords or identification cards (IDs) do not answer the needs of a modern security system, such as logging security management, protection of personal data and access security. Hence, there has been a striking progress in employing common computer-based methods for biometric identity detection, such as voice, signatures, fingerprints, face, palms of the hands and so forth [1–3]. The mentioned biometric characteristics like finger print, speech or face, are capable of being fake and their pattern could be copied. Hence, the new identity

detection methods based on biometric characteristics, such as cardiac signals, are under development. The electric potentials generated by all the muscles of the heart during each beat, collectively make up the electrocardiogram signal (ECG). The device that records this signal, is called electrocardiograph [4]. The ECG signal provides an important information about the heart rate and its performance [5,6]. In a typical signal, three waveforms can be seen in every heartbeat. P wave is the first one and the second waveform is the QRS complex and the T curve is the third [6,7]. The ECG signal varies in different individuals according to the position, size and anatomy of the heart as well as the relative weight, age, and the structure of the chest [6].

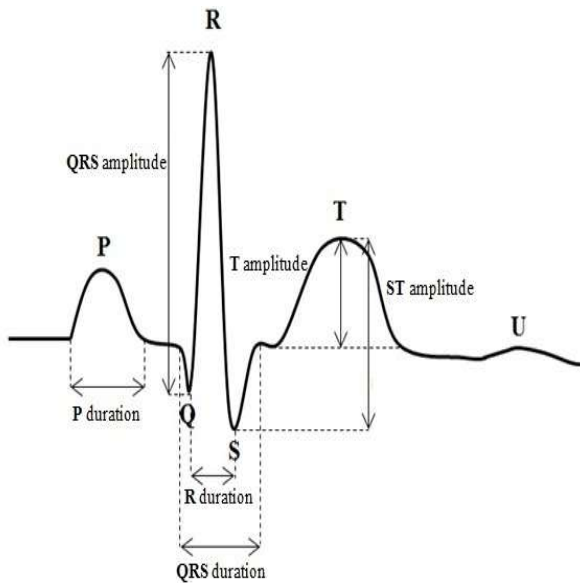
The uniqueness of ECG signals and robustness against copying or forgery have led to use them for constructing ECG-based identification algorithms [8–11]. A typical normal ECG signal is shown in Fig. 1 (a). ECG-based identification algorithms can be mainly summarized in four stages:

i) The ECG signal recording stage. ii) ECG preprocessing stage. iii) Feature extraction stage. iv) Compare and discern the identity of the input signal. Although most identification algorithms use various methods in steps 1, 2 and 4, but generally the nature of the above identification steps are almost identical and the major difference of these algorithms is the second stage feature extraction of ECG signal. The feature extraction algorithm can be categorized in two main groups [12]: 1- Transform-based algorithms [8,13,14]. 2) Algorithms based on waveform or morphology [15]. Transform-based algorithms take place on wavelet and frequency domain, in which frequency-based methods such as Discrete Fourier Transform and Discrete Cosine Transform are included. In waveform-based algorithms, some intervals between the specific points of the signal are used which these attributes give certain structural features of the signal.

Among the existing morphology-based methods, some of them can be mentioned such as the size of the QRS, the size of the T curve and the ST curve, duration of the R – peak and P – curve and also duration of QRS complex in the ECG signal. Using the characteristics based on the size are considered to be appropriate for

feature extraction due to their negligible change over the time [16,17]. These features are shown in Fig. 1 (b).

Biel, et al. came to 100% accuracy by employing 30 parameter morphology in a statistical society of 20 people [18]. Using wavelet transform in a population of 30 people, Chiu et al. achieved 100% accuracy for normal subjects and 81% accuracy for the patients [9]. Sasikala and Vahidabanu reached 99% accuracy by using morphological parameters PR, RQ, RS, RT, PS, TS, PQ and TQ as well as correlation coefficient parameter [6].



**Fig. 1.** ECG signal and its morphology parameters.

Shen and colleagues used the morphology parameters as well as benefit from a combined system, so accuracy of 100% and 95/3% were achieved for population of 50 and 168 respectively [19]. Using Fourier transform of autocorrelation coefficients and Euclidean distance, Belgasem and colleagues achieved 100% accuracy for population of 40 [8]. According to the results mentioned above, we can say that by using morphological parameters of the feature extraction, good accuracy could be achieved, especially for larger statistical community. Various methods for extraction of ECG morphological parameters have been evaluated in numerous articles [4,20,21]. However, although the curves in the ECG signal are distinguishing features of this signal, but due to various factors such as noise, change to the QRS complex waveforms over time, as well as similarities between the characteristics of the P curve, T curve and QRS complex, diagnosis of this curves is not easy to determine and there will be errors. In addition, due to the changes in these parameters in different cycles of heart rate, relative similarities between these parameters from different people may be

established which would reduce the performance of morphological characters for identification purpose [6,22,23]. In view of the restrictions proposed for morphological parameters, it seems that other parameters of signal should be used in parallel with these characteristics to increase the efficiency of these parameters, particularly in cases where the number of people increases.

Therefore, in this study, a new algorithm based on statistical parameters of signal and parameters scaling is proposed to increase the resolution of morphological parameters extracted from the ECG signals. In section 2 the methodology of the proposed algorithm will be explained and in section 3, the results of the proposed algorithm will be discussed.

## 2. Methodology

### 2.1. Database

In this research, the database ECG ID [24] is used. This database contains 310 records taken from 90 patients. Each record contains 20 seconds of ECG signal which is recorded with the frequency of 500 Hz and a resolution of 12 bits within range of the rated voltage. People aged between 13 and 75 years and 44 people of them are male and 46 people are female. The numbers of records for each person varies between 2 and 20 and were collected throughout the whole day and 6 months respectively. Full information and specifications of database can be found in [25].

A total of 69 people were selected from this database and a record is used per each person. For each person, half of the signal with the length of 10 seconds is used as a reference signal in the database, and the other half is used for evaluation and identification.

### 2.2. The proposed methodology

As mentioned in section 1, due to an error in recording the morphological parameters as well as possible similarities between these parameters in different people, one or more other parameters should be used in parallel with these parameters in identification algorithm, thereby, to increase the resolution of morphological parameters.

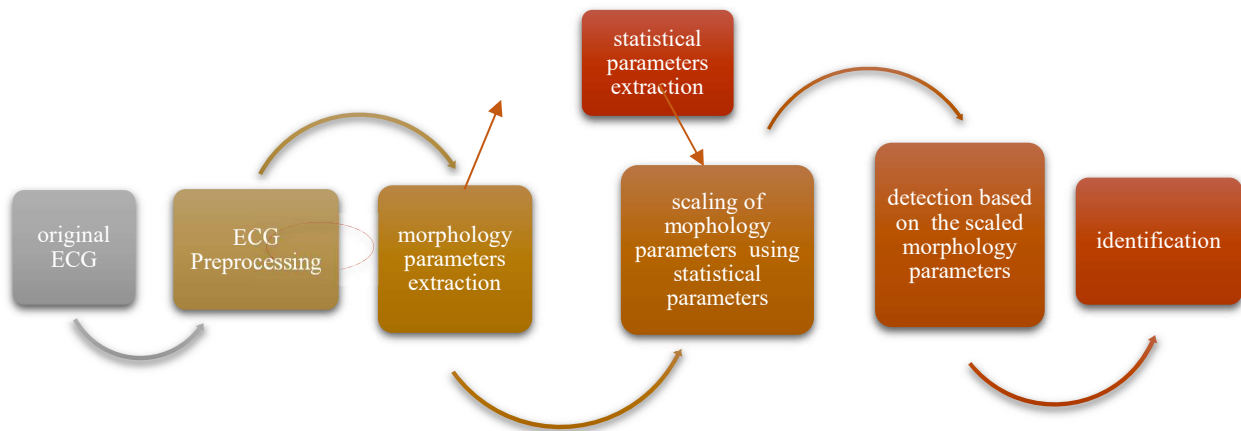


Fig. 2. Flowchart of the proposed algorithm

Therefore, in this study, a method based on scaling the morphological parameters using statistical parameters of signal is proposed. In this case, the selected morphological parameters are scaled as a desirable feature for the diagnosis of ECG signal identity, with the use of one or more statistical parameter. Finally, the identification is done based on the minimum Euclidean distance of scaled feature vectors, as shown in equation (1):

$$D_{A\_B} = \sqrt{\sum_{j=1}^n (x_j^A - x_j^B)^2} \quad (1)$$

Where  $D_{A\_B}$  is the Euclidean distance of the ECG feature vector of subject  $A$  from subject  $B$ ,  $n$  is the number of used morphological parameters, and  $x_j^A$  and  $x_j^B$  are the  $j$ -th components of feature vector for subject  $A$  and subject  $B$  respectively.

To identify based on this method, the Euclidean distance of feature vector of a certain signal is compared with the ECG feature vector of subjects in an ECG database, and the identity of the person who has the minimum Euclidean distance, is assigned to the test signal. The proposed algorithm can be summarized in the diagram as shown in Fig. 2.

### 3. Results and Discussion

At this point, first, the noise of ECG signals including baseline deviation, Electroencephalography noise (EEG), the electrode connection noise, muscles noise, internal amplifier noise, etc., was removed using a digital filter. So far, high-frequency noises such as EEG noise were excluded from the original signal by using a low-pass filter and also low frequency noises such as

baseline drift were removed using a high-pass filter. The noise of the AC power frequency (50 Hz) was removed with the help of *notch filters* [26–28]. An example of noisy ECG signal and denoised one is shown in Fig. 3.

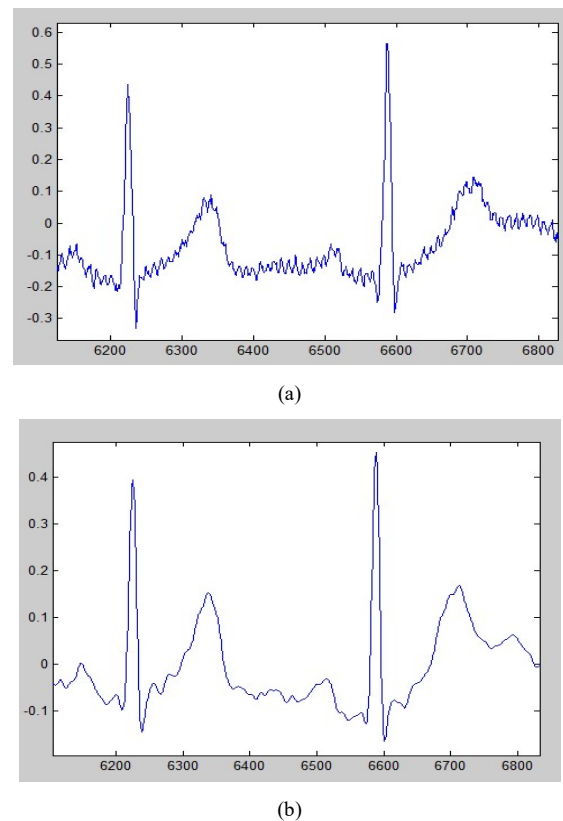
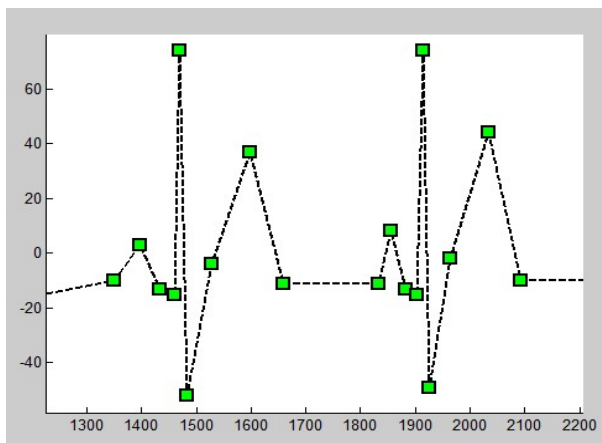


Fig. 3. ECG signal. (a). noisy signal. (b). signal after denoising

Then, P, QRS and T curves were also extracted from pre-processed signal using wavelet transform [4,6,22]. After determining the curves, both morphological and statistical parameters corresponding to one cycle of the ECG signal (including curves P, QRS and T) were obtained. Morphological parameters extracted from each cycle include the size of the QRS, the size of the curve T as the curve ST, a peak-R duration, a curve P duration, QRS complex duration.

The statistical parameters used were consisting of mean, standard deviation, entropy, range of variation, minimum, maximum, median and mode of each cycle. Curves extracted from a typical signal and morphological parameters used are shown in Fig. 4.



**Fig. 4.** Extraction of P, QRS and T curves from a typical signal and morphological parameters used

Next, each of the statistical parameters and also different combinations of them were applied to morphological parameters as the scale factor. Comparing with the results obtained the product of three parameters: mean, maximum and mode were selected as an optimum parameter to scale the morphological parameters. The result of identification for various people using three criteria (morphological parameters, statistical parameters and proposed method using Euclidean distance) is shown in Table 1.

**Table 1.** comparison of identification accuracy between three criteria: morphological parameters, statistical parameters and proposed method using Euclidean distance

Number of patients	morphological	statistical	Proposed method
20	95%	70%	100%
25	96%	68%	100%
30	96.67%	54.29%	100%

35	91.43%	53.33%	100%
40	85%	50%	100%
45	86.67%	48.89%	100%
50	84%	48%	100%
55	78.18%	50.90%	100%
60	78.33%	53.33%	100%
65	78.12%	54.68%	100%
69	75.36%	53.62%	100%

To ensure the accuracy improvement of the proposed method, the Generalized Regression Neural Network (GRNN) was also used to identify the same data. The results are given in Table 2. These results were achieved of 100 times repetitions using morphology parameters and the proposed method. The accuracy of results which include mean and standard deviation is achieved by means of 100 times repetition.

**Table 2.** comparison of Identification accuracy using morphology parameters, and the proposed method with the help of GRNN

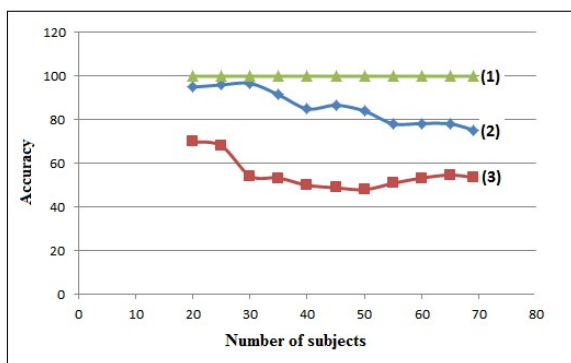
Number of patients	morphological	Proposed method + GRNN
20	85.3% ( $\pm 6.9\%$ )	86.8% ( $\pm 6.7\%$ )
25	83.7% ( $\pm 7.3\%$ )	84.4% ( $\pm 6.2\%$ )
30	80.7% ( $\pm 7.2\%$ )	84.2% ( $\pm 6.3\%$ )
35	79.3% ( $\pm 5.1\%$ )	83.9% ( $\pm 5.4\%$ )
40	75.8% ( $\pm 6.3\%$ )	80.1% ( $\pm 5.1\%$ )
45	75.1% ( $\pm 3.6\%$ )	81.3% ( $\pm 4.3\%$ )
50	73.8% ( $\pm 3.2\%$ )	80.4% ( $\pm 4.2\%$ )
55	72.9% ( $\pm 3.5\%$ )	80.1% ( $\pm 3.3\%$ )
60	71.7% ( $\pm 3.0\%$ )	79.3% ( $\pm 3.3\%$ )
65	70.9% ( $\pm 1.9\%$ )	79.1% ( $\pm 2.9\%$ )
69	70.3% ( $\pm 0.8\%$ )	78.6% ( $\pm 1.7\%$ )

According to Tables 1 and 2, in both algorithms, not only the accuracy is improved when using the proposed method, but the results have more stability vs. increment of statistical community. The graphical comparison of two algorithm using different methods is shown in Fig. 5. In plots of Fig. 5, the accuracy trend due to incrementing the number of people in statistical society is shown. Fig. 5(a) were plotted using the Euclidean distance and three criteria. On the other hand, in Fig. 5 (b), the accuracy trend is shown using GRNN and two criteria.

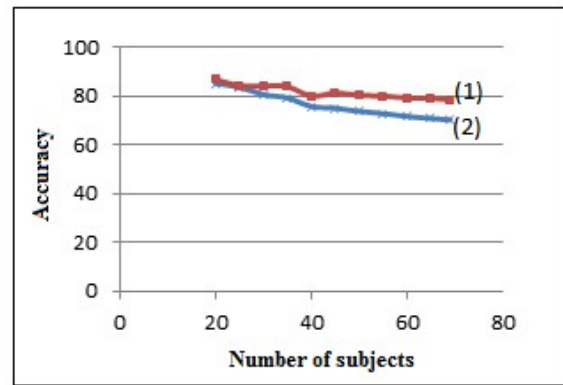
#### 4. Conclusion

In this paper an improved identification algorithm based on ECG signals was presented. The goal of proposed method was to increase the resolution of morphological parameters extracted from the ECG signals for better and more accurate identification. The proposed method was based on scaling the morphological parameters using statistical parameters of signal. Performance of the proposed method was evaluated in a statistical community including 20 to 69 people. In our largest statistical society (69 patients), the proposed algorithm using GRNN improved the accuracy up to 8.3% and the proposed algorithm using Euclidean distance criteria improved accuracy up to 24.64%. Hence, the increasing resolution of morphological parameters using proposed algorithm is clearly visible in both methods. On the other hand, with regard to the accuracy trend with the increasing number of people in the statistical society, it can be said that the proposed method has been more stable in spite of increment in the number of statistical community members and shows less variation.

In the Euclidean distance method, with an increase in the number of subjects up to 69 people, identity recognition has been 100% accurate without decreasing, while for the same number of subjects, we have precision reduction of 16.64% and 22% for morphology and statistical methods respectively. Also, using morphological parameters with the help of GRNN, as the number of subjects increase up to 69, the precision is reduces by 15.3% , while using the proposed method with the help of GRNN, we have precision decrement up to 2.8%, which confirms the more stability in results. Also it should be noted that the Euclidean distance criteria showed better results than the GRNN. Therefore, the proposed algorithm provides not only better resolution of morphology parameters but better stability in results as the number of subjects increased.



(a)



(b)

**Fig. 5.** The graphical comparison of two algorithm using different methods. Accuracy trend due to incrementing the number of people (a). using Euclidean distance. (b). using GRNN. (1) Proposed method (2) Morphological (3) Statistical

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