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Oral Topic: *Electrocardiography*

New approaches to ECG reconstruction for preserving diagnostic information

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Summary: In this work we propose novel algorithms for ECG reconstruction. A subset of 3 of the 12 ECG leads will be selected to reconstruct the remaining ones. Traditional models focus on minimizing the mean square error between the original signal and the reconstructed one. Instead, in this paper we focus on preserving diagnostic information from the ECG. In order to compare these new strategies in relation to traditional reconstruction methods, an error measure called “Weighted Diagnostic Distortion” (WDD) was used. It measures the quality of the reconstructed signal based on the accuracy of the position and amplitude of the main characteristics (such as start point, end and peak) of ECG waves (PQRST). The results show best performance for one of the methods here proposed.

Keywords: Weighted Diagnostic Distortion, ECG reconstruction, neural networks, genetic algorithms.

1. Introduction

Nowadays, the most common method for the diagnosis of heart disease is the analysis of the 12 leads of the ECG (I, II, III, aVR, aVF, aVL, V1, V2, V3, V4, V5, V6). To record 12 lead ECG, 10 electrodes are placed in certain areas of the body. However, some applications such as monitoring (ambulatory and continuous), and remote cardiac care require fewer electrodes. In this context, reconstruction of the missing ECG leads becomes a useful tool.

The most frequently used ECG reconstruction method is to perform a linear transformation on the input signals. Although linear models generally perform well, non-linear models can even improve the quality of the reconstructed signal. This claim is mainly based on the fact that the torso is an inhomogeneous conductor, which was originally demonstrated in the work of Burger and van Milaan [2]. In this context, neural networks are considered one of the most widely used non-linear models. Initially, Atoui [3] proposed a method based on conventional neural networks. A committee of several networks were trained with the backpropagation algorithm, and their outputs were averaged. Recently, in 2020, Lee [4] carried out a more complete work regarding the analysis of results. Neural networks are implemented with slight variations in the structure with respect to Atoui's work, and it demonstrates the robustness of this method in relation to the most relevant methods up to date. The disadvantage of this implementation is the high computational cost for the use of several networks (50 in Atoui's work). To solve this, a convolutional neural network model is proposed [5]. Other machine learning approaches are also proposed with a new training method based on the Monte Carlo algorithm, called General Vector Machine (GVM) [6]. GVM search the global minimum, and therefore doesn’t require the use of several networks.

In the state of the art, it can be verified that in most models the aim is to minimize the mean square error (MSE) and maximize the correlation. These measurements are useful in determining the similarity between the reference and the synthesized signal but the most important error criterion is based on similarity in the diagnosis made by expert cardiologists from both signals. In this direction, Zigel [1] introduces the WDD coefficient that compresses the diagnostic information from the parameters of ECG waves. Calculates the coefficient "mean opinion score" (MOS)[9], based on the results of surveys designed for experts to evaluate the quality of the synthesis according to the diagnosis made. Then, Zigel shows that the WDD coefficient is a better quality measure than those traditionally used (MSE and correlation), since it reports a higher correlation with MOS. This coefficient is frequently used [7,8] to evaluate the proposed methods.

Nevertheless, to the best of our knowledge there is no work focused on minimizing the diagnostic error in the training stage. This leads us to propose some new methods using neural networks models, where the loss function is based on the WDD.

2. Materials and Methods

2.1 Pre-proccessing

Before lead reconstruction, it is usual to do some pre-processing on 12 leads of the ECG. To eliminate low-frequency noise, the baseline of the ECG signal is determined through a low pass filter with a cutoff frequency of 0.7 Hz. A second order Butterworth low-pass filter with a 45 Hz cutoff frequency was applied to 12 leads to remove motion artifacts noise.

2.1. ECG Database

The database used to evaluate the methods is Lobachevsky University Electrocardiography(LUDB https://physionet.org/content/ludb/1.0.1/). This is better in several aspects than other public databases available. Various collections that are currently available in the public domain: MIT-BIH Arrhythmia Database, European ST-T Database, and QT Database, have certain limitations. MIT-BIH Arrhythmia Database, European ST-T Database have a markup only for QRS complexes. In turn, the QT Database contains annotations for P, QRS and T waves, but has only 2-lead recordings. The construction of the new LUDB database aims to eliminate these shortcomings. The database consists of 200 10-second 12-lead ECG signal records representing different morphologies of the ECG signal. The boundaries of P, T waves and QRS complexes were manually annotated by cardiologists for all 200 records. Also, each record is annotated with the corresponding diagnosis.

2.2. ECG wave delimitation

The calculation of the WDD coefficient depends on a previous phase to delimit the main waves of the ECG. The algorithm used to the ECG waves delimitation is based on the work of Laguna [10]. Detection of the QRS complex is performed first. T wave is recognized next, and, finally, the P wave. After detecting the ECG waves, it proceeds to search for their limits and peaks. The dyadic discrete wavelet transform (DWT) is calculated at scales 2^k, k=1,...,5. Then, with the use of thresholds and zero crossings of the DWT values in different scales, the limits and peaks of the ECG waves are found. We use the implementation of the python NeuroKit module(https://pypi.org/project/neurokit/).

2.3. The WDD Measure

The WDD measure is computed from the relevant diagnostic information of the ECG signal mainly distributed in the PQRST waves. The diagnostic features of PQRST waves are location, duration, amplitude, and shape. For each beat detected in the original and reconstructed signal, the features vectors (β for the original signal, $\hat{\beta}$ for the reconstructed signal) are found:

$$\beta = \left[\beta_1, \beta_2, \dots, \beta_p\right] \tag{1}$$

$$\hat{\beta} = \left[\hat{\beta}_1, \hat{\beta}_2, \dots, \hat{\beta}_p\right] \tag{2}$$

where p is the number of features in the vector. The diagnostic parameters used are: RR_{int}, QRS_{dur},QT_{int}, QT_{Pint}, RR_{int}, P_{dur}, PR_{int}, $QRS_{\text{peak\_no}}$, Q_{int}, QRS_{sign}, Δ_{exist}, T_{shape}, ST_{shape}, P_{shape}, RR_{int}, QRS^{+}_{amp}, $ST_{\text{elevation}}$and ST_{slope}. Table 1 shows an overview of all diagnostic parameters. These were chosen with the help of an experienced cardiologist.

The Weighted Diagnostic Distortion between these two vectors is :

$$WDD\left(\beta, \hat{\beta}\right) = \Delta\beta \frac{\Lambda}{tr[\Lambda]} \Delta\beta^T, \tag{3}$$

where $\Delta\beta$ is the normalized difference vector:

$$\Delta\beta = \left[\frac{\left|\beta_1 - \widehat{\beta_1}\right|}{max\left(\left|\beta_1\right|, \left|\widehat{\beta_1}\right|\right)}, \dots, \frac{\left|\beta_p - \widehat{\beta_p}\right|}{max\left(\left|\beta_p\right|, \left|\widehat{\beta_p}\right|\right)}\right], \tag{4}$$

and Λ is a diagonal weighting matrix.

2.4. Genetic algorithm with WDD coefficient (GAWDD)

This method consists of a neural network model where the search for optimal weights values is performed with a genetic algorithm. The loss function of the neural network is the value of the WDD coefficient. To calculate the WDD coefficient, it's necessary to estimate the limits of ECG waves previously (see diagnostic features used in Table 1). Since the gradient of the function used to delimit ECG waves cannot be calculated, the use of the backpropagation algorithm to train the network is not possible. This disadvantage justifies the use of the genetic algorithm to find the optimal value as an alternative.

The 2-point crossover method and the tournament selection algorithm are used. The score function used (eq. 5) includes the value of the WDD coefficient and a diversity measure to avoid rapid convergence. The diversity measure (Eq. 6) consists of calculating for each individual the average of the distance with the rest of the individuals. The gene values have a 10 bits resolution and the initial population has n=1400 individuals. A drawback of this method is the high computational cost due to the complexity of the fitness function, which involves the ECG waves delimitation for each beat. To deal with this problem, a variant is used, consisting of randomly selecting 10% of the beats for each generation.

$$f_i = (1-w)\left(1-\frac{WDD_i}{max(WDD_j)}\right) + w * d_i \quad (5)$$

where w is weighted parameter and d_i is the diversity measure for individual i:

$$d_i = \frac{\sum_{i != j} hamming(i,j)}{n-1} \quad (6)$$

$$hamming(i,j) = \frac{\delta(i,j)}{nbits} \quad (7)$$

where $\delta(i,j)$ is the number of different bits between individuals i and j, and nbits is the number of bits of the individuals.

2.5 Fine tuning with reduced WDD coefficient (FTWDDred)

This method consists of a neural network model with two training stages. In the first stage, the backpropagation method, with classic error loss function, is used with all points of the ECG signal. In the second stage, the backpropagation algorithm is also used, but only the characteristic points of the ECG waves are used for error computation. This is made possible by the use of the Lobachevsky University Electrocardiography Database with the annotations file of ECG wave marks. So we avoid the use of the wave delimitation algorithm prone to induce artifacts in the neural network learning process due to the difficulty of this task.

Table 1. Description of the diagnostic features (10mm=1mV)

Feature's serial number	Feature symbol	Feature description	Units
1	RR_{int}	The time duration between the current and the previous location of the R waves	msec
2	QRS_{dur}	The time duration between the onset and the offset of the QRS complex	msec
3	QT_{int}	The time duration between QRS_{on} and T_{off}	msec
4	QTp_{int}	The time duration between QRS_{on} and T_p	msec
5	P_{dur}	The time duration between P_{on} and P_{off}	msec
6	PR_{int}	The time duration between P_{on} and QRS_{on}	msec
7	QRS_{peaks}	The number of peaks and notches in the QRS complex	(>= 1)
8	QRS_{sign}	The sign of the first peak in the QRS complex	(1 or −1)
9	$\Delta_{wave?}$	The existence of delta wave [28]	(0 or 1)
10	T_{shape}	The shape of T wave (see table 2)	
11	P_{shape}	The shape of P wave (see table 2)	
12	ST_{shape}	The shape of ST segment (see table 2)	
13	QRS^{+}_{amp}	The maximum positive amplitude of the QRS complex	mm*
14	QRS^{-}_{amp}	The minimum negative amplitude of the QRS complex	mm
15	P_{amp}	The amplitude of P wave	mm
16	T_{amp}	The amplitude of T wave	mm
17	$ST_{elevation}$	The ST elevation [29]	mm
18	ST_{slope}	The ST slope [29]	mm/sec

3. Results

For the evaluation of the methods, leads I, II and V2 are used to reconstruct the remaining leads. For the analysis of the results, lead V1 is discarded due to the low performance of the wave delimiter in this lead. For the evaluation of the methods, 25% of the records from the database are randomly selected. A comparison is made between the two here proposed methods and other two relevant state of the art methods: Atoui's Neural Networks (AtouiNN) and Linear Regression. Table 2, 3 and 4 show the results of the MSE, Correlation and WDD measures respectively. We observe that the FTWDDred method has the best performance in the WDD and Correlation measures, but not with respect to the MSE measure. The worst performance relative to MSE is due to FTWDDred targeting the diagnostic areas of the ECG in the second phase. Therefore, since the MSE is measured in the entire signal, it is expected that AtouiNN is better with respect to this measure than FTWDDred. We also note that the difference between FTWDDred and AtouiNN is small in the WDD measure. Therefore, the test was repeated 30 times to verify if the differences between the results of these methods are significant with the t-test. The results show that only lead V3 shows significant differences for alpha = 0.05.

Table 2. WDD for each method(lower values are better)

Methods	V3	V4	V5	V6	Mean
Linear Model	**12.57**	12.46	9.26	8.05	10.59
AtouiNN	13.45	9.69	**8.19**	7.22	9.64
FTWDDred	12.95	**8.50**	8.52	**7.17**	**9,28**
GAWDD	12.98	11.57	8.54	7.74	10.21

Table 3. Correlation for each method(higher values are better)

Methods	V3	V4	V5	V6	Mean
Linear Model	0.90	0.86	0.90	0.92	0.89
AtouiNN	0.91	0.88	**0.92**	0.93	0.91
FTWDDred	**0.92**	**0.89**	**0.92**	**0.94**	**0.92**
GAWDD	0.82	0.74	0.72	0.84	0.78

Table 4. MSE for each method(MSE value * 100, lower values are better)

Methods	V3	V4	V5	V6	Mean
Linear Model	0.22	0.29	0.24	0.21	0.24
AtouiNN	0.17	**0.27**	**0.18**	**0.17**	**0.20**
FTWDDred	**0.16**	0.28	0.19	**0.17**	0.20
GAWDD	0.45	0.52	0.46	0.38	0.45

Figures 1 and 2 show that in some areas of the PQRST waves, the FTWDDred method better approximates the original signal than the AtouiNN. We observe that this improvement occurs mainly in the QRS peaks, also in the T peak, although to a minor extent. This result corresponds to what is expected according to the approach of the FTWDDred method. Since the information on the location, duration and shape of the ECG waves isn't used, only an improvement in the amplitude of the points used to perform the fine adjustment is obtained.

3. Conclusions

A novel approach is proposed and evaluated to improve ECG reconstruction focusing on relevant diagnostic information. The best performance was achieved with the FTWDDred method, but the GAWDD method didn't improve the results of the Atoui neural network. This is caused by limitations of the ECG wave delimitation algorithm. In the analysis of the results, it was shown that the improvements of the FTWDDred are only with respect to the amplitude of the ECG waves, mainly in the QRS. This drawback leads to the study of other alternatives in future works.

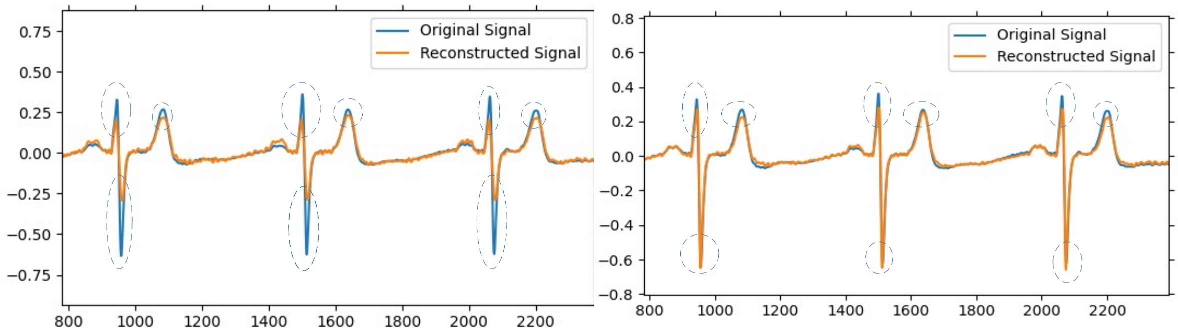

Fig. 1. Record 169 signal reconstructed with AtouiNN (left) and FTWDDred (right) methods.

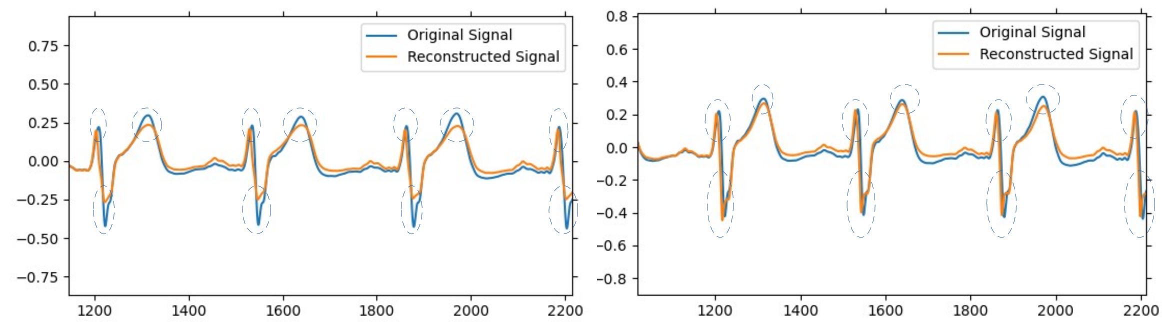

Fig. 2. Record 185 signal reconstructed with AtouiNN (left) and FTWDDred (right) methods.

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