A Neural Network Approach for Patient-Specific 12-Lead ECG Synthesis in Patient Monitoring Environments

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Abstract

Background: In recent years, there has been a growing interest in developing accurate methods for the synthesis of the 12-lead ECG from a minimal lead-set to improve patient monitoring in situations where the acquisition of the 12-lead ECG is difficult or impractical. Objective: This paper presents a method that aims to derive the standard 12-lead ECG from a pseudo-orthogonal 3-lead subset via a non-linear patient specific reconstruction method that is based on the use of artificial neural networks (ANN). Methods: We train and test the ANN over a 300 adult patients study population. We then assess the performance of the ANN based ECG synthesis method in comparison with the multiple regression based method and test for statistical differences between the two methods using the paired Student's t-test. Results: The ANNs achieved high overall accuracies for all the testing sets. Moreover, the difference in accuracies between both methods is statistically significant ($p \leq 0.001$). Conclusions: The encouraging results reported here suggest that the artificial neural networks represent a rather interesting and very promising approach to improve the synthesis of the 12-lead ECG.

1. Introduction

In home care or ambulatory situations, performing the recording of the standard 12-lead electrocardiogram (ECG) is often difficult and impractical. It would be valuable to have a minimal lead set from which the 12-lead ECG can be reconstructed. This is nowadays a great challenge for e-health projects like EPI-MEDICS [1] that aim at developing intelligent systems for the early detection and management of cardiac events.

Moreover, the EPI-MEDICS [2] demonstrated that a 4-electrode, 3-lead pseudo-orthogonal lead set configuration based on: DI, DII and V2 contained as much diagnostic information as the 12-lead ECG for the diagnosis of acute myocardial infarction and of transmural ischemia. The project also proved that the retained (DI, DII, V2) subset contains enough information for synthesizing the standard 12-lead ECG, the only ECG representation that cardiologists can accurately analyze and interpret.

Previously published investigations [3, 4] on the synthesis of the 12-lead ECG generally adopted linear-based techniques such as multiple regression. However, most of these studies have been assessed on continuous 3-lead or standard 12-lead ECG recordings where the training and testing were conducted on the same data. Also, none of these studies tried to evaluate the accuracy of lead reconstruction over a long time period.

In addition, even though linear descriptions yielded high success rates over a limited time period (24 hours) when electrode positions remain in the same place [4], such methods would face serious challenges when the difference in acquisition time between ECGs reaches several months for serial ECGs. Generally, the specificity and uniqueness of the human body: factors such as the patient gender, age, morphology, medical history, etc. definitely influence the physiological and electrical relationships between the lead signals. Also, noise or other signal artifacts generated by possible electrodes displacements may generate a significant difference between ECG signals over time and thus hinder a high quality synthesis.

Under such circumstances, non-linear methods such as artificial neural networks are believed to further enhance the approximation and compensate the conventional linear approaches weaknesses [5]. In fact the scientific literature is full of examples where the non-linear routines provide a more efficient alternative for conventional approaches [6].

In this paper we present a method that aims to derive the standard 12-lead ECG from a pseudo-orthogonal 3-lead subset via a non-linear patient specific reconstruction method that is based on the use of artificial neural networks (ANN). We then assess the performance of the ANN based ECG synthesis method in comparison with the multiple regression based method at the issue of the learning phase and on ECGs recorded at a few months interval.

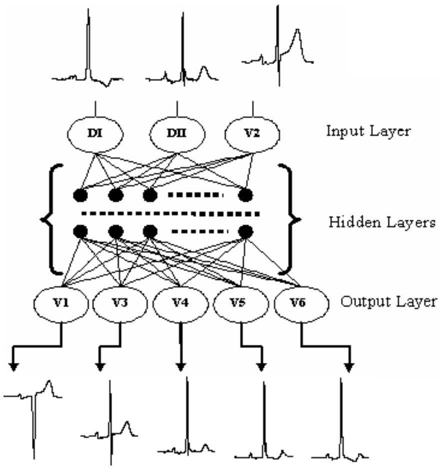

Figure 1. ECG synthesis via ANN

2. Materials and methods

2.1. Study population

We used a subset of a 12-lead ECG database [7] of patients who presented to an emergency department of a university hospital, and who were categorized as non acute myocardial infarction patients. Each patient had a previous baseline ECG recording hereafter called reference ECG. From this database, we extracted 3 subsets of 100 patients. Data sets DS1 and DS2 were obtained by random selection. DS3 was build up by selecting 100 patients that did not show significant serial changes between their two ECG records, according to the CAVIAR serial analysis method [8]. The study population thus consists of 300 pairs of ECGs (112 male, 188 female) with a mean age of 79 years (range 40-96 years) recorded in average at one year interval (range 0-64 months). Each ECG record consists in a 1 sec duration representative cycle of the original 10 sec ECG record. Sampling rate was 1000 s/sec.

2.2. Methods

2.2.1. Neural networks architecture design

To synthesize the (V1, V3, V4, V5, V6) ECG signals from the recorded (DI, DII, V2) 12-lead ECG subset, we used a set of multi-layer feed-forward artificial neural networks (ANN) (Figure 1) trained by means of a supervised back-propagation algorithm. Each individual ANN consists in one input layer with 3 input neurons (one for each recorded signal), an output layer with 5 output neurons (one for each derived signal), and h hidden layers (typically, h=1 or 2). This choice was dictated by a series of considerations based on previous experiences in synthesizing non-linear biomedical signals and on a critical literature review.

However, it is well known that training ANNs is a very difficult task that can easily lead to overdesigning the networks and result in poor generalization capabilities. We thus decided to build up an ANN ensemble that consists of a committee of 50 ANNs of the figure 1 type. The outputs of the ANN committees are obtained by summing (and dividing by 50) the outputs of the 50 individual ANNs. This averaging process has proven to provide, as a result of the central limit theorem, higher performances than each individual network sub-solution [9].

2.2.2. Neural networks training

Ideally, we would need 3 serial ECGs per patient for deriving a patient specific ANN ensemble: one for training the network, one for stopping the learning process in order to avoid network overdesign, one for testing the generalization capacity of the trained network. Unfortunately, our database comprised only two serial ECGs per patient. To overcome this difficulty, we adopted the following two steps strategy:

1. ANN dimensioning: We used DS1 to determine the best network architecture and to fix the number of iteration K to use during the learning process. Learning was performed by training each individual ANN to synthesize the training reference ECG. Stopping was performed by monitoring the reconstruction error on the test ECG (the emergency ECG). This procedure was repeated for each of the h*n*t (h=number of hidden layers; n=number of neurons per layer; t=number of transfer functions) architectures, for 50 different networks biases and weights initializations and for each of the patients of DS1. The best h*n*t configuration is the one that minimizes the reconstruction error on the synthesized leads of the test ECG of DS1. The number of iterations K is determined by computing for each patient the average of the maximum number of iterations for each of the 50 individual ANNs of the committee and by averaging these values over the 100 patients of DS1.
2. Verification and validation: The aim of the second step is to verify if the optimal ANN architecture determined during step1 performs well on data sets different from the data set used for the ANN dimensioning. It consists of two successive operations:
   (a) Determination, for each patient, of a patient specific ANN committee of 50 ANNs obtained by training the ANNs to synthesize the reference ECG. The architecture of each individual ANN is the one determined in step1 and the number of iterations is a fixed value equal to K.
   (b) ANN committee performance evaluation. The ANN committees determined during step2.a are then used to synthesize the "missing" leads of the test ECGs, and these synthesized ECG leads are compared to the original leads

of the test ECGs. These procedures are applied in turn for each patient of data sets DS2 and DS3. This approach guarantees a fair evaluation of the reconstruction capability of the patient specific ANN committee: the test ECGs of DS2 and DS3 have never entered the training process. All the processings were performed by using the Matlab ANN toolbox.

(c) Neural networks performance assessment. The quality of the ECG leads reconstruction capacity of the ANN committees was evaluated in three ways:

i. By assessing the Root Mean Square (RMS) error and the correlation coefficients between the original leads and the reconstructed leads of DS2 and DS3.

ii. By comparing these values with the ones obtained by using patient-specific multiple linear regression models of the type:

$$V_i = a_{i0} + a_{i1}DI + a_{i2}DII + a_{i3}V2 \tag{1}$$

where the patient-specific a_{ij} coefficients are derived from the reference ECGs and then applied on the test ECGs.

iii. By performing a paired t-test and a trimmed paired t-test to determine if the RMS errors of the ANN and the linear regression based reconstruction methods are statistically different. The trimmed t-test is used to overcome the t-test sensitivity to outliers. Both tests are performed with the BMDP statistical software package.

3. Results

3.1. Architecture dimensioning

The best ANN architecture was determined experimentally bytraining h*n*t different architectures obtained by varying the number of hidden layers (h=1, 2), the number of neurons per layer (n=3, 5, 8, 10, 15) and the transfer functions (t=linear, sigmoid: tansig, logsig). As usual in approximation tasks, we selected a linear activation function for the output neurons. The best results were obtained for h=1 hidden layer of 15 neurons, a sigmoid transfer function and K=75 iterations.

3.2. Performance assessment

Table 1 displays the RMS values and the correlation coefficients for the two studied methods. It shows the superiority of the ANN committees over the regression based synthesis method. Interestingly, the values obtained for DS3 are much better than the values obtained for DS2 and even DS1, the training set indicating that a substantial part of the differences between the reconstructed and the original leads might be explained by electrodes displacements and/or changes in the heart position rather than changes in accuracy. Table 2 summarizes the results

		DS1		DS2		DS3	
	Lead	**RMS**	**r**	**RMS**	**r**	**RMS**	**r**
	V1	67	.96	75	.95	55	.98
A	**V3**	102	.95	135	.94	93	.96
N	**V4**	107	.93	142	.93	90	.97
N	**V5**	85	.95	113	.95	74	.98
	V6	64	.97	91	.96	53	.98
	V1	72	.95	81	.95	62	.97
R	**V3**	111	.94	148	.93	93	.95
E	**V4**	127	.91	169	.91	102	.96
G	**V5**	97	.94	127	.94	84	.97
R	**V6**	70	.95	95	.95	58	.98

Table 1. Root Mean Square Error (in μV) and correlation coefficients between the original and the reconstructed V1,V3...V6 leads for the ANN committee and multiple regression based models for data sets DS1, DS2 and DS3.

of the paired and trimmed paired t-tests. The difference in accuracies between the ANN and the regression based methods is statistically significant (p<0.001). In other words, neural networks committees significantly improve the ECG synthesis.

	Lead	**DS1**	**DS2**	**DS3**
P	**V1**	0.012	0.012	$< 10^{-5}$
A	**V3**	0.016	0.043	0.992
I	**V4**	$< 10^{-8}$	10^{-3}	$< 10^{-4}$
R	**V5**	$< 10^{-4}$	5.10^{-4}	$< 10^{-4}$
W	**V6**	$< 10^{-4}$	0.078	0.011
T	**V1**	0.001	7.10^{-4}	$< 10^{-7}$
R	**V3**	3.10^{-4}	$< 10^{-5}$	0.991
I	**V4**	$< 10^{-4}$	$< 10^{-7}$	$< 10^{-8}$
M	**V5**	$< 10^{-6}$	$< 10^{-4}$	$< 10^{-7}$
M	**V6**	$< 10^{-5}$	0.040	$< 10^{-4}$

Table 2. Pairwise comparisons of the RMS values of the ANN committee and multiple regression based synthesis methods (p-values).

4. Discussion

Although the RMS values obtained in table 1 seem to be higher than in some publications using the linear regression model, our findings indicate that the standard and synthesized ECG leads are very similar (Figure 2). The differences in terms of RMS errors are sufficiently small, taking into consideration the nature of the ECGs in the study population, so that they would not be considered diagnostically important in the majority of cases. The reason for the differences between our findings and the other authors findings is due to the fact that these authors

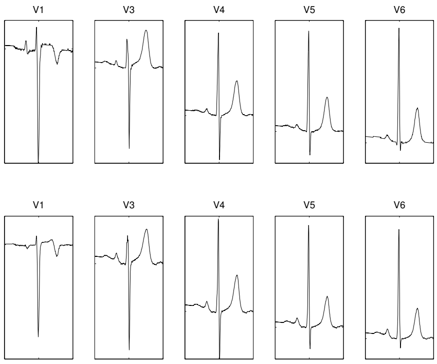

Figure 2. Original (top) vs synthesized (bottom) ECG leads from a test ECG from data set DS3.

did not test their models on an independent test set. In the best case the test was performed at a few minutes difference but without changing the electrode placements.

4.1. Limitations

In some cases (less than 5%), the ANN failed to accurately synthesize missing leads with a RMS error greater than 200 μV. Also around 6% of the cases, the multiple regression model outperformed the ANN. These failures can be explained by the fact that we lack a third ECG recording to be used as a validation set to avoid over-fitting and to improve the generalization capabilities. It may also be due to changes introduced by electrode misplacements. Nevertheless, the encouraging results reported here suggest that the artificial neural networks represent a rather interesting and very promising approach to improve the synthesis of the 12-lead ECG.

4.2. Implementation choices

From a technical viewpoint, integrating technologies such as neural networks committees in telemedecine systems to calculate the patient-specific transformation matrix tends to be costly in terms of disk space and computation time during the training phase. To overcome such an obstacle, a grid-based solution could be very efficient since it provides dependable, consistent, pervasive and inexpensive access to high-end computational capabilities. The ANN committee concept fits very well the parallelism requirements inherent to the grid concept.

5. Conclusion

This paper introduces an original approach of ECG synthesis via artificial neural networks. We believe that this is the first report of the use of artificial neural networks for ECG synthesis in the context of patient monitoring. The main strength of our method lies in its capability to model the complex non-linear relationships between ECG leads that the various regression-based techniques failed to capture.

Preliminary experiments show that synthesized ECGs are accurate and can be used in a 3-lead ECG recording procedure. Further work is needed to optimize and validate the ANN architecture and initializations by using a larger and more representative database.

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