SURFACE ELECTROCARDIOGRAM RECONSTRUCTION FROM CARDIAC PROTHESIS ELECTROGRAMS

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Abstract: Implantable cardiac devices (ICD) are constantly integrating new functionalities and, in particular, allow the recording and storage of the intracardiac electrical activity, namely the electrogram (EGM). However, these EGM are not exploited in clinical practice and, in order to perform a patient's check-up or adjust ICD parameters, the physician will use the surface electrocardiogram (ECG) as the main reference signal. In this paper, we address the problem of reconstructing a surface ECG from a set of local EGM, available in the prothesis. Two methods are presented, based on a least square estimation of a linear transfer function between an EGM lead and an ECG lead and a multilayer perceptron. Results show that reconstruction is well performed by both approaches for patients presenting sinus rhythm. However, for patients presenting polymorphic arrhythmia, least square approach leads to high distorsions, whereas neural network approach provides a good reconstruction with low mean square errors.

Introduction

Implantable cardiac devices (ICD), such as pacemakers or implantable cardioverter defibrillators, are constantly integrating new functionalities to improve the delivered therapy and, more recently, to acquire and analyze the patient's physiological data in order to ease the clinical follow-up. One of the most important data acquired are the electrograms (EGM), which are a recording of the intracardiac electrical activity, measured between a couple of electrodes implanted in the pacemaker leads (bipolar EGM), or between the pacemaker housing and one of the available intracardiac electrodes (unipolar EGM). In some cases, a short segment of one or two EGM leads can be stored in the ICD memory, when a particular kind of activity is detected (i.e. during an arrhythmia episode or before the delivery of a defibrillation shock). Stored EGM signals can be sent by telemetry to a pacemaker programmer or a monitoring device that can display the ICD data or send these data to the clinician.

During a typical pacemaker clinical follow-up, physicians analyze the data acquired by the ICD (stored in the ICD memory or acquired in real-time) in order to diagnose the current state of the patient and optimize the pacing parameters. However, the direct interpretation of the acquired EGM signals is very difficult because: *i)* beat morphologies are different from those observed on the surface ECG (which remains the main reference signal for the analysis of the cardiac electrical activity) and *ii)* intracardiac signals reflect the electrical activity of a given part of the heart, showing only a local view of the observed phenomena. The acquisition of a standard surface ECG is thus performed during these follow-ups, to evaluate the evolution of the patient's pathology.

In this work, we study the problem of the reconstruction of the surface ECG from a set of EGM leads. This reconstruction would allow to reduce the time spent during pacemaker follow-up, thus reducing costs, to ease the analysis of the EGMs transmitted by the ICD in telemedical applications and could help to improve the detection algorithms embedded into the ICD processor. Different methods to reconstruct the standard 12-lead ECG from a subset of non-standard ECG leads have been proposed in the literature. They range from linear regression [1], non linear filtering to artificial neural networks (ANN) [2, 3]. However, to our knowledge, the reconstruction of surface ECG leads from intracardiac EGM has not been addressed.

In general, it can be considered that the surface ECG lead $y(t)$ can be obtained as the output of a transfer function $h(t)$, applied to the EGM lead $x(t)$, in the presence of an additive noise $b(t)$, as presented in Figure 1.

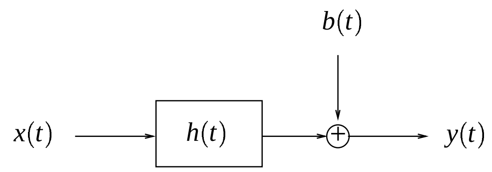

Figure 1: Problem formalization

The problem of the reconstruction of the ECG signal can thus be formalized as the estimation of the transfer function $\hat{h}$, based on available samples of $x(t)$ and $y(t)$. The application of $\hat{h}$ on $x(t)$ will provide us an estimation of the surface ECG, $\hat{y}(t)$. Two approaches will be studied in this work for obtaining $\hat{h}$: a linear approach, based on a least square estimation of a filter h, and a nonlinear approach, based on an artificial neural network (ANN), implemented as a multilayer perceptron. In both cases, a beat segmentation phase is applied, using a matched filter, to obtain a sequence of N QRS detection instants $\tau_i, i = 1, ..., N$ from the selected EGM lead. Beat segments $x_i(t)$ were constructed for each beat i, by applying a window of length L on the EGM signal: $x_i(t) = x(\tau_i - L/2, ..., \tau_i + L/2 - 1)$. The same process was applied to the ECG signal, to obtain target segments $y_i(t) = y(\tau_i - L/2, ..., \tau_i + L/2 - 1)$.

Nevertheless the proposed method requires a full database which is presented in the next section. Methods and results are then detailed.

Database description

Recently, the construction of a multi-channel signal database containing ECG signals and new EGM leads has been started in our laboratory with a previous study [4]. This study had for objective to directly extract new features from a set of EGM signals for arrhythmia recognition.

Each record of the database is composed of 6 surface ECG channels (leads I, II, III, aVR, aVL and aVF) and 2 to 13 EGM leads, depending on the ICD type. Signals are acquired during the implant of ICDs with a GE Cardiolab station, located in the electrophysiology laboratory. Records have a typical duration of 30 seconds and are sampled at 1000 Hertz.

To this date, data from 14 patients and 3 different ICD types have been acquired: 9 single-chamber pacemakers, 4 double-chamber pacemakers and 2 cardioverter defibrillators. Most of the patients (10) presented sinus rhythm and 6 patients presented cardiac arrhythmia: atrial fibrillation episodes (patients 7, 12, 13 and 14), supraventricular tachycardia (patient 5) and non-sustained ventricular tachycardia (patient 8). Patients 3, 10, 12 and 13 present a bundle branch block (BBB).

This diversity of ICDs leads to a heterogeneity on the acquired EGM leads. Table 1 summarizes the available EGM leads with respect to the ICD type.

Figure 2 presents a sample of recorded data. For this patient (patient 3), all EGM leads are available.

ECG estimation by linear filtering

The problem that we propose to study can be modeled by equation (1) where $x(t)$ is a EGM lead and $y(t)$ is an ECG lead (cf Figure 1). The filter $h(t)$ modelises the propagation channel and $b(t)$ is an additive noise:

$$y(t) = (x * h)(t) + b(t). \quad (1)$$

After discretization, equation (1) can be rewritten:

$$y = S_x h \quad (2)$$

where S_x is the convolution matrix of $x(t)$, whose column contains the delayed versions of $x(t)$. If $h(t)$ is assumed

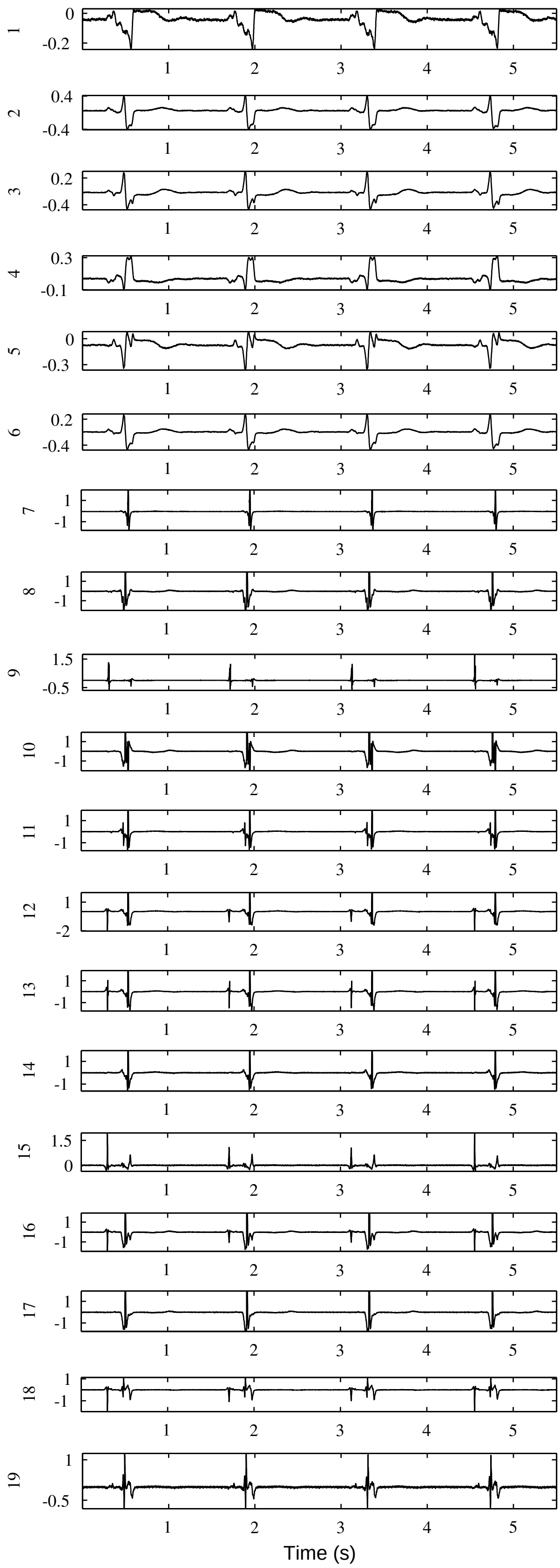

Figure 2: Example of recorded data for patient 3, presenting right BBB: 1-6 ECG leads, 7-19 EGM leads

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Table 1: Available EGM leads with respect to the ICD type (1ch: single-chamber, 2ch: double-chamber and Def: cardioverter defibrillator). RA=right atrium, RV=right ventricle, Coil 1= proximal coil, Coil 2 = distal coil

	EGM lead	1ch	2ch	Def
7	RV, bipolar (RVBip)	x	x	x
8	Coil 1 vs Coil 2 (Coil1Coil2)			x
9	RA, bipolar (RABip)		x	x
10	Coil 2 vs RV (Coil2RV)			x
11	Coil 1 vs RV (Coil1RV)			x
12	RA-dist vs. RV-prox (RARV)		x	x
13	RA-prox vs RV-dist (RApRVd)		x	x
14	RV, unipolar (RV)	x	x	x
15	RA, unipolar (RA)		x	x
16	RA vs. Coil 2 (RACoil2)			x
17	Coil 2, unipolar (Coil2)			x
18	Coil 1, unipolar (Coil1)			x
19	RA vs. Coil 1 (RACoil1)			x

linear, an estimation of H can be obtained by the least square algorithm:

$$\hat{h} = (S_x^T S_x)^{-1} S_x^T y. \qquad (3)$$

In order to reconstruct the surface ECG from the EGM signal, we estimate the filter h from a sample of data, and then apply the estimated $\hat{h}$ to the recorded EGM. We have used a beat-based approach as described previously, with $L = 300$ (i.e. 0.3 sec.).

Figures 3 and 4 show two examples of reconstructed QRS beats on patient 3, presenting a sinus rhythm and a right BBB, and on a polymorphic arrhythmic patient, patient 8, with the least square algorithm. Three types of reconstruction are shown:

- (c) a filter is estimated on each beat i between the EGM beat $x_i(t)$ and the ECG beat $y_i(t)$
- (d) a filter is estimated on the first beat between $x_1(t)$ and $y_1(t)$ and applied to all the signals $x_i(t)$
- (e) the reconstruction is performed with the mean filter, obtained by averaging the filters obtained in (c).

Figure 3 shows that whatever the filter $\hat{h}$, a very good reconstruction is observed with monotype beats. On the contrary, with several types of morphology, a mean filter, as expected, is an unacceptable solution (Figure 4(e)). Otherwise, it is worth to notice that estimation of $\hat{h}$ for each couple produces good results (Figure 4(c)). This suggests to develop a multireconstruction filter stategy which is not a valid solution in ICD.

Furthermore, we experimentally observed that a reconstruction of the whole beat (P and QRS wave) was not possible from a single filter. However, by using RA Bipolar lead and a specific filter, P wave reconstruction can be carry out. This approach requires two distinct filters (one for the P wave and one for the QRS complex) and has not been retained as it is not a feasible solution for embedded processing on the ICD.

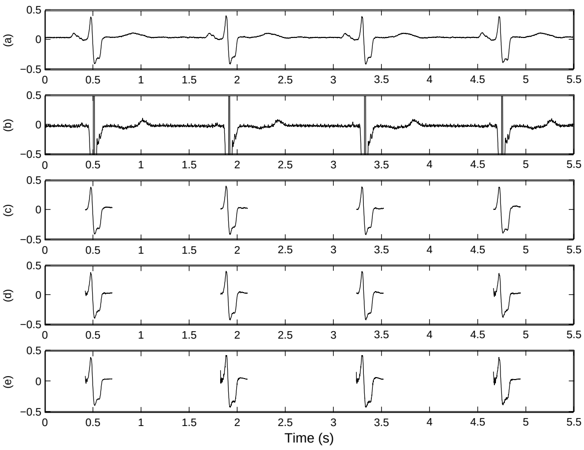

Figure 3: ECG reconstruction on patient 3, presenting a sinus rhythm with right BBB: (a) ECG lead II, (b) EGM lead Coil2, (c) ECG reconstruction QRS by QRS, (d) with first QRS, (e) with mean filter

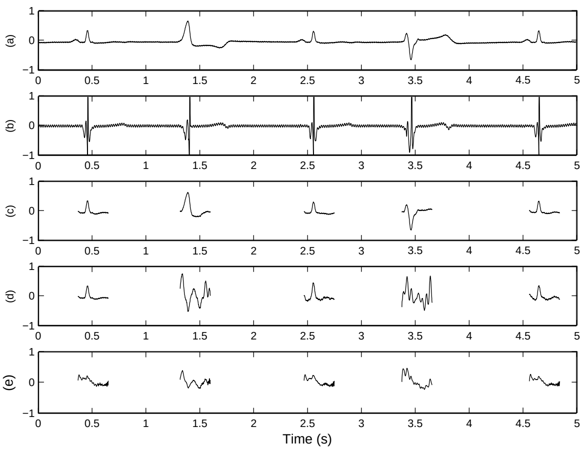

Figure 4: ECG reconstruction on patient 8, presenting a polymorphic arrhythmia (NSVT): (a) ECG lead I, (b) EGM lead RV, (c) ECG reconstruction QRS by QRS, (d) with first QRS, (e) with mean filter

ECG estimation by ANN approach

The universal approximation capabilities of the multilayer perceptron (MLP) makes it an interesting choice for modelling nonlinear systems. In particular, MLPs have shown to be useful in solving pattern matching problems, even in the case of multiple, concurrent pattern morphologies [5]. In this section, a classical MLP implementation is employed to reconstruct the surface ECG $y(t)$ from a given EGM signal $x(t)$, in a beat-to-beat basis (reconstructing the P-wave and the QRS complex of each beat).

A classical methodology for the development of ANNs has been applied. It can be divided into the following steps: *i)* signal pre-processing, *ii)* construction of a training set and a test set, *iii)* optimization of the ANN configuration and *iv)* ANN training.

Signal pre-processing: Beat segments $x_i(t)$ and $y_i(t)$ are subsampled at 100Hz and low-pass filtered at 30Hz. Signals are normalized, so that they will have zero mean and unity standard deviation. These subsampled versions of $x_i(t)$ and $y_i(t)$ are used as input and target vectors, respectively.

Construction of a training set and a test set: The training data-set is constructed by selecting two thirds of the beat segments from the whole database (i.e. with data from all patients). The rest of the data is used for testing purposes.

Optimization of the ANN configuration: The retained MLP structure is based on three layers: an input layer consisting of L samples of vectors $x_i(t)$; a hidden layer of N^H neurons with tangent sigmoid transfer functions, and an output layer, with L linear neurons that produce directly the output vector $\hat{y}_i(t)$, to be compared to the target ECG, $y_i(t)$. A set of experimental trainings was performed to define appropriate values for L and N^H. Two main criteria were used to choose the best network configuration: *i)* the visual difference observed between the measured ECG and the computed ECG signals and *ii)* the mean square error (MSE) between $\hat{y}_i(t)$ and $y_i(t)$. The best results were obtained with the following values: $L = 100$ (e.g. the equivalent of 1 second) and $N^H = 3$. Figure 5 shows a graphic representation of the proposed ANN.

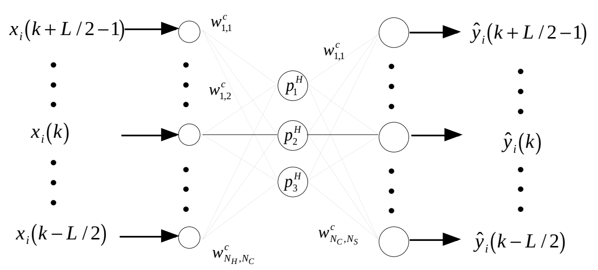

Figure 5: General structure of the proposed ANN

ANN training: The ANN is trained using a standard backpropagation algorithm with an adaptive learning rate. The number of training periods is set to 1000.

Figure 6 shows the result obtained with the example of Figure 4. We observe that the ANN is able to reproduce the three different QRS morphologies in this example with a relatively low distortion.

The global training has been applied using all the available combinations of EGM and surface ECG leads, in order to study if a particular EGM lead provides a better ECG reconstruction. Results are assessed using the MSE between $\hat{y}_i(t)$ and $y_i(t)$. Figures 7 to 9 show boxplots representing the mean of the MSE calculated for all surface ECG leads, for each patient of the database, using a given EGM lead as input to the ANN. For EGM leads RVBip and RV, the 14 patients are available. For EGM lead Coil2, 10 patients are available.

We can observe that the ECG reconstruction for pa-

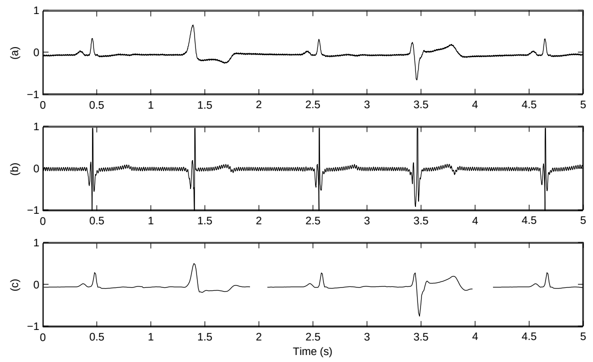

Figure 6: ECG reconstruction on a polymorphic arrhythmic patient (patient 8): (a) ECG lead I, (b) EGM lead RV, (c) ECG reconstruction with ANN approach

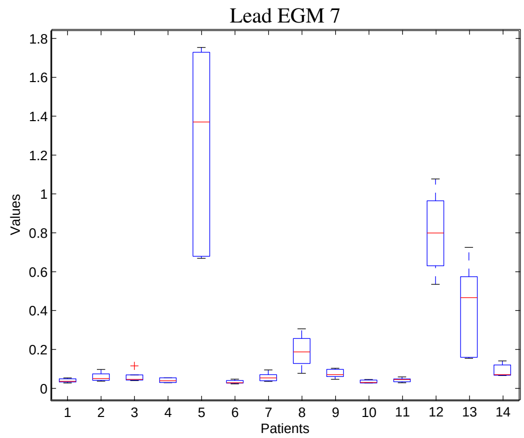

Figure 7: Boxplots of the mean of the MSE obtained with EGM lead RVBip

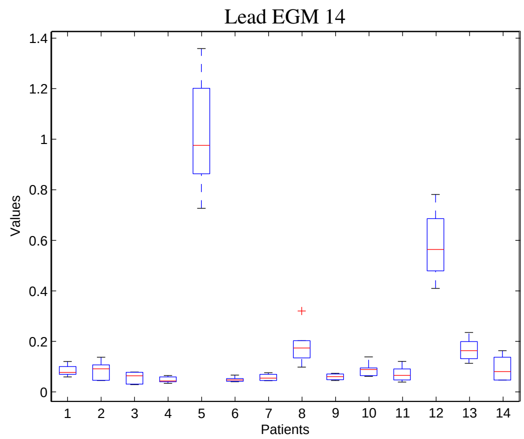

Figure 8: Boxplots of the mean of the MSE obtained with EGM lead RV

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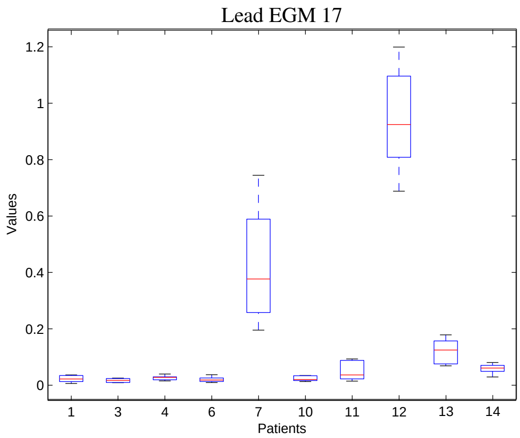

Figure 9: Boxplots of the mean of the MSE obtained with EGM lead Coil2

tient 5 presents the worst results. This is the patient who suffers from supra-ventricular tachycardia. ECG reconstructions for patients 12 and 13 (present in the three boxplots) have also low performance. These patients present atrial fibrillation and BBB. In general, performance are lower for patients presenting cardiac arrhythmia, but no conclusion regarding a particularly appropriate EGM lead could have been found.

Patient-specific training: We performed a patient-specific training, (i.e. a training on data issued from a single patient), which would be possible to perform, in clinical practice, after the ICD implant.

A comparison between patient-specific training and global (non patient-specific) training is represented in Figures 10 and 11. The comparison is presented for leads RVBip and RV, available for all patients, and for reconstruction of ECG lead II.

It is observed that, except for patient 11, the patient-specific neural network produces lower MSEs than the MSE of the global network, with both EGM leads RVBip and RV. Similar results were obtained with all ECG leads. In the case of patient 5, MSE is divided by a factor 5.

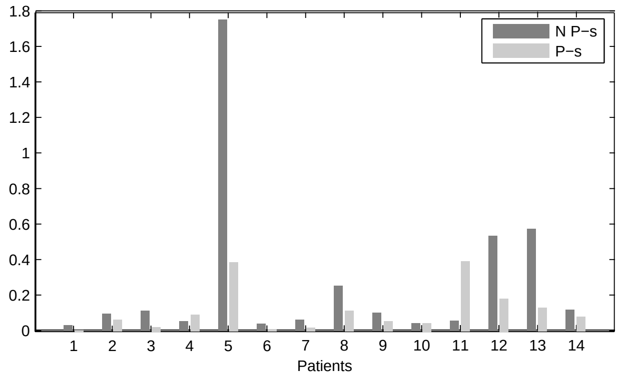

Figure 10: Mean square error for non patient-specific (N P-s) and patient-specific (P-s) training with ECG lead II and EGM lead RVBip

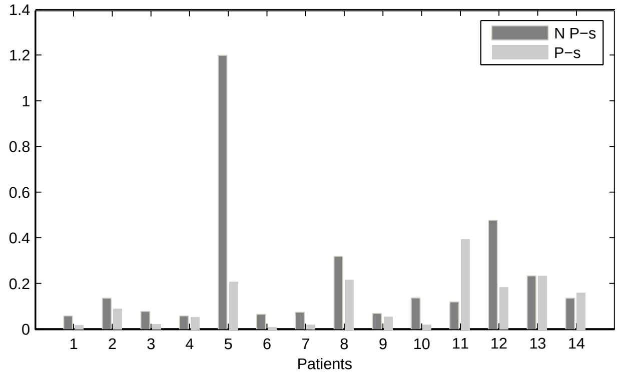

Figure 11: Mean square error for non patient-specific (N P-s) and patient-specific (P-s) training with ECG lead II and EGM lead RV

follow-up. For clinical use, we could imagine to perform the patient-specific training of the network just after the ICD implant. However, the evolution of the transfer function should be studied upon long durations. In the same way, neural network methods require an extensive EGM/ECG database for both training and testing and the actual database must be extended.

Conclusion

In this paper, we propose to reconstruct surface ECG by the use of internal EGM recorded by cardiac prothesis. Two methods have been presented. The first one, based on a least square estimation of a linear transfer function between an EGM lead and an ECG lead, provides good results for patients presenting sinus rhythm. However, in the case of polymorphic arrhythmic patients, least square approach leads to high distorsions whereas the second one, the neural network approach, provides a good reconstruction with low mean square errors.

One of the clinical interests of the proposed approach may be to obtain a surface ECG without the presence of a practician, which could be useful for telemedical

References

[1] STEFAN P., NELWAN, JAN A. KORS, SIMON H. MEIJ, JAN H. VAN BEMMEL, and MAARTEN L. SIMOONS. Reconstruction of the 12-lead electrocardiogram from reduced lead sets. *Journal of Electrocardiology*, 37:11–18, 2004.

[2] H. ATOUI, J. FAYN, and P. RUBEL. A neural network approach for patient-specific 12-lead ecg synthesis in patient monitoring environments. In *Computers in Cardiology*, volume 31, pages 161–164, 2004.

[3] VASQUEZ C, HERNANDEZ A, MORA F, CARRAULT G, and PASSARIELLO G. Atrial activity enhancement by wiener filtering using an artificial neural net-

work. *Biomedical Engineering, IEEE Transactions*, 48:940–944, 2001.

[4] KABALU-BADIAMBILA G. Proposition de nouvelles méthodes pour la caractérisation d'arythmies ventriculaires par les prothèses cardiques. Master's thesis, Université d'Angers, LTSI-Inserm, Rennes, 2004.

[5] T. SRIKANTH, S. A. NAPPER, and H. GU. A bottom-up design of neural network based ecg beat and rule-based rhythm classifier. *International Journal of Bioelectromagnetism*, 4(1), 2002.