# COMPARISON OF FOUR ESTIMATORS OF THE 3D CARDIAC ELECTRICAL ACTIVITY FOR SURFACE ECG SYNTHESIS FROM INTRACARDIAC RECORDINGS

A. Kachenoura<sup>(1,2)</sup>, F. Poré $e^{(1,2,)}$ , G. Carrault<sup>(1,2,3)</sup> and A.I. Hernández<sup>(1,2,3)</sup>

<sup>(1)</sup>INSERM, U642, Rennes, F-35000, France;
<sup>(2)</sup>Université de Rennes 1, LTSI, Rennes, F-35000, France;
<sup>(3)</sup>INSERM, CIT804, CIC-IT de Rennes, F-35000, France.

# ABSTRACT

The aim of this study is to facilitate the home follow-up of patients treated with cardiac implantable devices. A new procedure to synthesize 12-lead ECG from intracardiac EGM is proposed. It is based on the estimation of: (i) a 3D representation of the cardiac electrical activity both for ECG (VCG) and EGM (VGM), and (ii) the transfer function between the VGM and the VCG. The extraction of VCG and VGM is performed by comparing four different algorithms based on PCA and ICA, whereas the non-linear transfer function between VCG and VGM is estimated using a specific neural network. Results demonstrate the effectiveness of the proposed method in comparison with our previous work. Indeed, the correlation coefficients, between the real ECG and the synthesized ECG, lie between 0.78 and 0.99, whereas correlation coefficients of the previous method (combining PCA and linear Wiener filter) lie between 0.6 and 0.94.

*Index Terms*— Surface ECG, Intracardiac EGM, ICA, PCA, Neural Network.

# 1. INTRODUCTION

Patients treated with Cardiac Implantable Devices (CIDs), such as Bi-ventricular Pacemakers (BivP) and Defibrillators (BivD) used in the cardiac resynchronization therapy require regular hospital visits to perform patient's follow-up, to monitor whether the CID is working optimally and, eventually, to modify the pacing parameters. Current developments have for objective to propose accurate methods for remote follow-up of these patients so as to reduce the health care costs. Since the physician consider the surface ElectroCardio-Gram (ECG) as the reference signal for the analysis of the cardiac activity and since the CIDs only provide intrathoracic ElectroGrams (EGM), the aim of this paper is to synthesize a standard set of 12lead ECG from EGM data in order to provide a less expensive and less time-consuming setup for monitoring the patient's cardiac electrical activity, that could be useful in a telemedecine application. It is worth noting that the EGM provides local information on the electric activity of a group of cardiac cells, and, up to now to our knowledge, the cardiac arrhythmias recognition based on EGM is still an unsolved problem.

Several methods dealing with the synthesis of the 12-lead ECG have been reported, including linear and non-linear filtering [1–5], but these methods share some limitations. Those based on a few surface ECG leads [3, 4] require the acquisition of clinical data either in an attended laboratory setting or by using an ambulatory electrocardiography device (Holter monitor). In the method given in [2] the 12-lead ECG is synthesized by using only one EGM lead, which makes the result strongly dependent on the chosen EGM. Regarding the method proposed in [1], the authors reconstruct the 12-lead ECG from a set of EGM leads by using linear filtering. However, in a

real application, noise or artifacts generated by electrode displacement, changes on the patient's body position or cardio-respiratory interactions may influence the relationships, over time, between the EGM and the surface ECG. Thus stochastic and non-linear phenomena crop up, and time series dynamics cannot be robustly described using classical linear filtering. In order to overcome these shortcomings, this paper presents a novel procedure to synthesize the 12-lead ECG from a set of intracardiac EGM, acquired from CID electrodes. This procedure is based on: (i) the extraction of a three dimensional (3D) representation of cardiac electrical activity [6] both from surface ECG (which is called VectorCardioGram, VCG) and from EGM (which is called VectorGram, VGM [1]), and (ii) the estimation of the Transfer Function (TF) between VGM and VCG by using a dynamic Time Delay artificial Neural Network (TDNN). Four different methods are proposed and compared for the first step: Principal Component Analysis (PCA) [7], Robust Principal Component Analysis (RobPCA) [8], Independent Component Analysis based on Second Order statistics (ICASO) [9] and Independent Component Analysis based on Fourth Order statistics (ICAFO) [10]. A quantitative evaluation of the proposed procedure is also proposed, as opposed to our previous work [1] where the filter estimating the TF between VGM and VCG was based on a linear time invariant filter.

# 2. PROBLEM STATEMENT AND BACKGROUND

#### 2.1. Signal model

The problem that we propose to study can be modeled as follows:

$$\boldsymbol{x}[m] = \mathcal{F}(\boldsymbol{s}[m]) + \boldsymbol{\nu}[m] \tag{1}$$

where the outputs  $\{x[m]\}_{m\in\mathbb{N}}$ , representing the surface ECG, are considered as an unspecified non-linear function  $\mathcal F$  of the inputs  $\{s[m]\}_{m\in\mathbb{N}},$  representing the EGM data, plus an additive white noise  $\{\nu[m]\}_{m\in\mathbb{N}}.$  The problem of the surface ECG signal synthesis can thus be approached by a classical two-step method, including a training step and a synthesis step. The training step aims to identify the function  $\mathcal{F}(\hat{\mathcal{F}}, \text{ which will be thus specific to each patient})$ by using a dataset of x[m] (ECG) and s[m] (EGM) signals, simultaneously acquired in an attended laboratory setting during the implant of the CID. The synthesis step is devoted to the estimation of surface ECG,  $\hat{x}[m]$ , by exploiting only the EGM, s[m], and the estimate,  $\hat{\mathcal{F}}$ , of  $\mathcal{F}$ . It should be noticed that it will be possible to acquire, in the near future, the set of s[m] signals directly from the CID by telemetry. Nevertheless, before detailing these two steps, let us, briefly, introduce the four algorithms used for the extraction of the 3D cardiac electrical activity and the TDNN architecture, and justify why these tools are used in our approach.

#### 2.2. Extraction of the 3D cardiac electrical activity

The VCG is an orthogonal lead system that reflects the electrical activity in the three perpendicular directions X, Y, and Z. Although the 12-lead ECG is considered as the reference setup for the analysis of the cardiac electrical activity, the VCG contains useful information for some applications [6, 11]. Indeed, it is well-known that the VCG is superior to the ECG in showing phase differences between electric events in different parts of the heart. In addition, contrary to the standard 12-lead ECG, the analysis based on VCG loops has been found to (i) better compensate the changes in the electrical axis caused by various extracardiac factors [12], such as respiration, body position, electrode positioning, and so forth, (ii) give a compact representation of the cardiac electrical activity, minimizing storage needs, and (iii) provide a solution to the time synchronization problem which arises in cardiac data. These characteristics of the 3D representation of the cardiac electrical activity seem to be useful in our case (see point (i) and (ii) just above). The VCG can be obtained by methods which establish a transformation from the standard ECG leads to the VCG domain and vice versa, such as Dower Transform (DT) [13] and Levkov Transform (LT) [14]. Since such methods do not exist in the case of EGM, we propose to test and compare different algorithms (PCA, RobPCA, ICASO and ICAFO) to extract the VGM and the VCG.

#### 2.3. Principal component analysis

PCA is one of the oldest and most popular techniques in statistical data analysis, features extraction and data compression. The purpose of PCA is to derive a relatively small number of decorrelated linear combinations (principal components) of a set of random zero-mean variables while retaining as much of the information from the original variables as possible. Typically, the PCA of vector  $\boldsymbol{x}[m] = [\boldsymbol{x}[m]_1, \cdots, \boldsymbol{x}[m]_N]^T$  consists in looking for an overdetermined  $(N \times P)$  (i.e.  $P \leq N$ ) orthonormal linear transform  $\boldsymbol{W}$  such that the P components of the vector  $\boldsymbol{z}[m] = [\boldsymbol{z}[m]_1, \cdots, \boldsymbol{z}[m]_P]^T = \boldsymbol{W}^T \boldsymbol{x}[m]$  are mutually uncorrelated. It is straightforward to show that the PCA problem can be converted to the eigenvalue problem of the zero time-lag covariance matrix  $\boldsymbol{R}_{\boldsymbol{x}}[0]$ . Thus, if we denote  $[\boldsymbol{e}_1 \dots \boldsymbol{e}_P]^T$  the eigenvectors of  $\boldsymbol{R}_{\boldsymbol{x}}[0]$  corresponding to the eigenvalues  $(\lambda_1, \dots, \lambda_P)$  where  $\lambda_1 \geq \dots \geq \lambda_P$ , the first principal component of  $\boldsymbol{x}[m]$  is  $\boldsymbol{z}_1[m] = \boldsymbol{e}_1^T \boldsymbol{x}[m]$ . Likewise, the *P*-th principal component is obtained by  $\boldsymbol{z}_P[m] = \boldsymbol{e}_p^T \boldsymbol{x}[m]$ .

In practice, the covariance matrix of the noise  $\nu[m]$  can not be precisely estimated, especially in the case where the number of sensors N is equal to the number of sources P. The effect of the additive white noise cannot be removed in the conventional PCA [7] which only exploits the zero time-lag covariance matrix  $R_x[0]$ . This limitation is considered in [8] where the authors propose, under the assumption of colored components, a new algorithm (RobPCA) which is unaltered by an additive white noise. More precisely, the idea of the RobPCA is to search an  $N \times P$  orthonormal linear transform W from the eigen-structure of J time-delayed covariance matrices  $R_x[\tau_j]$ , where  $\tau_j$  are non-zero positive integers.

## 2.4. Independent component analysis

The ICA of  $\boldsymbol{x}[m] = [\boldsymbol{x}[m]_1, \cdots, \boldsymbol{x}[m]_N]^{\mathsf{T}}$  consists in looking for an overdetermined  $(N \times P)$  mixing matrix  $\boldsymbol{A}$  and a P-dimensional source vector process  $\boldsymbol{s}[m] = [\boldsymbol{s}[m]_1, \cdots, \boldsymbol{s}[m]_P]^{\mathsf{T}}$  whose components are the most statistically independent as possible so that the linear observation model below holds:

$$\forall m \in \mathbb{N} \ \boldsymbol{x}[m] = \boldsymbol{A} \, \boldsymbol{s}[m] + \boldsymbol{\nu}[m] \tag{2}$$

Where  $\boldsymbol{\nu}[m] = [\boldsymbol{\nu}[m]_1, \cdots, \boldsymbol{\nu}[m]_N]^{\mathsf{T}}$  is noise vector process independent from the source process. In other words, ICA consists in searching for a  $(N \times P)$  separator matrix  $\boldsymbol{W}_o$  such that  $\boldsymbol{y}_o[m] = \boldsymbol{W}_o^{\mathsf{T}} \boldsymbol{x}[m]$  is an estimate of the source vector  $\boldsymbol{s}[m]$ .

Two classical ICA techniques are exploited in this study. The second order blind identification algorithm (ICASO) [9], is based on the joint approximate diagonalization of a set of delayed covariance matrices of the data. This algorithm seems to be very efficient in the case of colored sources. The second technique (ICAFO) is based on Fourth Order (FO) statistics. It explicitly maximizes a contrast function based on the FO cumulants of the data by rooting successive polynomials [10]. It should be noted that both techniques require a prior standardization procedure of the data (the standardization procedure may be viewed as a mere PCA [10]). This step is also used in ICA to reduce the dimension of the data.

#### 2.5. Dynamic Time Delay artificial Neural Network

It is well-known that feed-forward artificial Neural Networks (ANNs) with an input layer, a single hidden layer, and an output layer may be used as universal function approximators, under very general conditions for the activation functions [15]. Time Delay ANNs (TDNN) are a particular implementation of feed-forward ANNs, in which delayed versions of the input signals are presented at the input layer of the network. TDNNs have thus an extended capability for time series processing, with respect to feed-forward ANNs, as they include a representation of the k past samples of each input signal. More details on this type of ANN can be found elsewhere [15].

#### **3. DATABASE**

A dataset issued from 14 patients (P1 to P14) is used for evaluating the performance of the proposed method and for the comparison of four 3D cardiac electrical activity estimators. The ECG and EGM were simultaneously recorded with a GE Cardiolab station during the implant of CIDs with an initial sampling rate equal to 1000 Hz and then subsampled at 100 Hz and low-pass filtered at 45 Hz. Each record of the database is composed of 12 standard surface ECG channels, namely I, II, III, AVR, AVL, AVF, V1, to V6 and four to seven EGM electrodes depending on CID type. Three different CID types have been used: a triple chamber defibrillator for patients P1, P5, P6, P7, P8, P12 and P13, a triple chamber pacemaker for P9, P10 and P14 and a dual chamber pacemaker for patients P2, P3, P4 and P11. We also observed that nine patients of the database present an ECG with a sinus rhythm (P1 to P9), whereas two patients (P10 and P11) present a polymorphic beat sequences. Premature Ventricular Beats (PVB) are also detected on three patients (P12 to P14).

Each patient's file is segmented into two blocks: the first one contains L = 20 heartbeats of concurrent ECG and EGM signals and is used in the training step, the second block contains Q = 11 beats and is devoted to the synthesis step.

#### 4. PROPOSED METHOD

#### 4.1. Training step

This step can be divided into two sub-steps : i) the estimation of the 3D cardiac electrical activity (VCG and VGM) and ii) the estimation of the TF between the VGM and the VCG.

*Estimation of the VCG and the VGM:* Let us consider that  $x[m] = [x[m]_1, \dots, x[m]_N]^T_{m=1,\dots,M}$  and  $s[m] = [s[m]_1, \dots, s[m]_K]^T_{m=1,\dots,M}$  where  $N \ge 3$  is the number of ECG leads,  $K \ge 3$  is the number of EGM leads and M is the number of records. This estimation is performed by using one of the four algorithms a (a represents one

of the four estimation algorithms) described earlier (PCA, RobPCA, ICASO and ICAFO) on  $\boldsymbol{x}_{ECG}[m]$  and  $\boldsymbol{x}_{EGM}[m]$  so that the following results hold:

$$\boldsymbol{z}_{VCG}[m] = \boldsymbol{W}_{VCG}^{a} \boldsymbol{x}[m]$$
$$\boldsymbol{z}_{VGM}[m] = \boldsymbol{W}_{VGM}^{a} \boldsymbol{\bar{s}}[m]$$
(3)

Only the three principal component (for PCA and RobPCA) and three independents components (for ICASO and ICAFO) are analyzed. This provides a  $(N \times 3)$  matrix  $W^a_{VCG}$  and a  $(K \times 3)$  matrix  $W^a_{VGM}$ .

Estimation of the TF between the VGM and the VCG: Three different MISO (Multi-In Single-Out) systems, M1, M2 and M3, between the three row input vector  $z_{VGM}[m]$  and each row of the output vector  $z_{VCG}[m]$  are estimated in this step. For each patient, three TDNN are trained by using the VCG and the VGM issued from 20 heartbeats of concurrent ECG and EGM. Each TDNN is defined with an input layer of  $N_I = 3 \times k$  samples, a hidden layer of  $N_H$  neurons with a sigmoid activation function and one linear output neuron. Different structures are tested for the TDNN, by changing k and  $N_H$ . The best performance (trade-off between quality of reconstruction and computing time of the training step) is obtained for k = 4 samples at the resampled frequency of 100 Hz and  $N_H$  of around 50 neurons. In this paper, the approach proposed by D. MacKay [16] and implemented in Neural Network Toolbox of Matlab is used to improve the generalization of our procedure and to avoid overfitting.

# 4.2. The synthesis step

Let's suppose that we only observe the EGM of Q successive heartbeats (in our case Q = 11). The synthesis step, devoted to the estimation of surface ECG by exploiting the EGM and different parameters identified in the training step, is divided in three parts: (i) the linear transforms  $W^a_{VGM}$  (for all four methods) are applied on EGM, which provides us the  $(3 \times M')$  VGM matrix (where M'is the number of records of the EGM used in the synthesis step), (ii) the  $(3 \times M')$  VCG matrix is estimated by using M1, M2 and M3 systems and (iii) the surface ECG is obtained by multiplying the pseudo-inverse of each linear transform  $W^a_{VCG}$  with the estimated VCG.

# 5. RESULTS

#### 5.1. Quantitative performance evaluation

In this section, we compare the performance provided by our procedure, when we use the four different methods (PCA, RobPCA, ICASO and ICAFO) proposed to extract the 3D cardiac electrical activity, in the case of patients with sinus rhythm, patients with polymorphic beat sequences and those with PVB. We also evaluate the quality of the 12-lead ECG reconstruction as a function of the number and location of EGM electrodes exploited by our procedure. This last point is investigated in this paper in order to evaluate the behavior of our procedure in some practical situations where the CIDs provide only three electrodes.

Figure 1 (a), (b) and (c) show examples of real surface ECG (blue solid line) and synthesized ECG (red dashed line) for a patient with sinus rhythm (P5), a patient with polymorphic beat sequences (P11) and a patient with PVB (P13), respectively. In these examples, the synthesized ECG is obtained from all the available EGM electrodes and by using PCA to extract the VCG and the VGM. Clearly, for P5 and P11, the synthesis errors are practically insignificant. Regarding P13 our procedure seems to provide less reliable estimates for the abnormal beat. However, the behavior of our procedure is promising since the synthesized pathological morphologies are very different from sinus beats and the ECG wave durations are preserved.

Thus, even if our procedure is not able to exactly reproduce some beat morphologies, it can be used to detect the presence of abnormal ECG beats. In addition, the preservation of the ECG wave durations can be particularly useful to characterize certain pathologies from synthesized beats.



**Fig. 1**. Examples of the synthesized ECG (Real surface ECG: blue solid line and synthesized ECG: red dashed line): (a) patient with sinus rhythm (P5), (b) patient with polymorphic beat sequences (P11) and (c) patient with PVB (P13).

In order to compare the quality of the 12-lead ECG synthesis of our procedure obtained by using the four estimators of the 3D cardiac electrical activity as a function of the number of EGM electrodes, our procedure is applied to all the database by exploiting: i) all the available EGM electrodes and ii) three EGM electrodes (those commonly available on triple chamber pacemakers and triple chamber defibrillators [1]). Figure 2 (a) shows that, for all patients, the behavior of the PCA, RobPCA, ICASO and ICAFO using all EGM is equivalent. The same result is also observed when only three EGM are used (figure 2 (b)). Another interesting result is the equivalent performance obtained using three EGM in comparison to those obtained exploiting all available EGM. Figures 2 (a) and (b) show also the very good behavior of our procedure both for the patients with sinus rhythm and with polymorphic beat sequences (correlation coefficient between the real ECG and the synthesized ECG is above 0.95). For patients P12, P13 and P14, the proposed procedure seems to be less effective in comparison to other patients (correlation coefficient is about 0.84). This result is essentially due to the fact that P12, P13 and P14 present PVB, having different morphologies.





**Fig. 2.** Correlation coefficient between real ECG and synthesized ECG, for each patient, using PCA, RobPCA, ICASO and ICAFO: (a) exploiting all the available EGM electrodes and (b) exploiting three EGM electrodes.

#### 5.2. Comparison of the non-linear filter and the linear filter

As shown in the previous section, the behavior of our procedure, when using PCA, RobPCA, ICASO and ICAFO to estimate the 3D electrical cardiac activity, can be considered equivalent. Thus, using the PCA 3D cardiac activity estimator, we propose to compare the influence of the TF estimation (linear Wiener filter [1] and the TDNN) between the VGM and the VCG.

It appears in figure 3 that the non-linear method leads to better results. Indeed, for all the database and whatever the number of EGM leads (figure 3 (a) and figure 3 (b)), correlation coefficients of the non-linear method lie between 0.78 and 0.99, whereas correlation coefficients of the linear filtering method lie between 0.6 and 0.94.



Fig. 3. Comparison of the non-linear filtering methods and the linear filtering method: (a) exploiting all the available EGM electrodes and (b) exploiting three EGM electrodes.

#### 6. DISCUSSION AND CONCLUSION

We propose in this study a patient-specific method to synthesize a standard 12-lead ECG from EGM. The method is based on the 3D representation of the intracardiac (VGM) and the surface (VCG) electrical activity. Based on the orthogonal characteristic of the VCG, we compare four different orthogonalization algorithms, namely PCA, RobPCA, ICASO and ICAFO. The obtained results exhibit that the performance of the four algorithms are equivalent. This can be explained by the fact that the processing of the eigenvalues of the covariance matrix  $R_{\alpha}$  of the 12-lead ECG shows that signal energy is only concentrated on three main components. All these results strengthen the idea that any orthogonalization algorithm can be able to estimate the 3D cardiac electrical activity. We also reported (see section 5.2) that the non-linear filter is more effective than the linear filter.

Our procedure presents good behavior both for patients with sinus rhythm and patients with polymorphic beat sequences. Regarding the patients with PVB, our method provides promising results. Preliminary results show that the synthesized abnormal morphologies are very different from sinus beats. In addition, the ECG wave durations of the normal/abnormal beat seem to be preserved, which is useful for a diagnosis purpose (such as the characterization of bundle branch block). Another interesting result shows that the performance of our procedure by using only three EGM electrodes or a high number of EGM are quasi-identical. This last result is very interesting in the practical case where most of CIDs provide only three implantable electrodes.

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