Synthesizing Surface ECGs from Intracardiac Electrograms Using an Adaptive Filter Method

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Abstract

This study investigates the feasibility of synthesizing surface ECG (SECG) from the intracardiac electrogram (IEGM) measured by the implanted device. Using an adaptive filter approach, we characterize the optimal filters relating the representative IEGM templates and the desired SECG templates. The optimal filters, which vary from sample to sample and are specific to event types, are then used to process the IEGM input to generate the pseudo-ECG output. The algorithm was preliminarily evaluated on experimental data collected from an anaesthetized pig and in selected data from the Ann Arbor Electrogram Libraries. In all tested cases, the morphological features of the pseudo-ECG are highly comparable to the SECG, and clinically relevant cardiac rhythm information was preserved. The IEGM derived pseudo-ECG may provide useful diagnostic information and facilitate implant device follow-up.

1. Introduction

The surface ECG (SECG) is routinely measured during pacemaker follow-up to examine the status of the electrical conduction system of the heart, and to confirm the normal functionality of the implant device. However, the recording of SECG is time consuming, and is susceptible to motion artefacts and noise interference.

Thus it is clinically attractive to generate the SECG-like signal, or pseudo-ECG, without the need to attach the skin electrodes to the patients. There have been considerable efforts in the pacemaker industry to develop the pseudo-ECG feature, for example, to record far-field cardiac signal by means of subcutaneous electrodes [1]; to approximate the SECG by the far-field intracardiac electrogram (IEGM) [2,3]; and to post-process the IEGM to estimate the SECG through signal processing techniques such as neural network or fuzzy logic [4].

In this study, we investigate the feasibility of synthesizing pseudo-ECG using adaptive filter method, which characterizes the optimal filters relating the representative IEGM templates and the desired SECG templates. The algorithm was preliminarily evaluated on data collected from an acute swine model and in selected data from the Ann Arbor Electrogram Libraries (Ann Arbor, Michigan).

2. Methods

2.1. Algorithm overview

The algorithm consists of two stages: filter characterization and active filtering.

In filter characterization stage, the algorithm takes representative beats of IEGM and the desired beats of SECG as input. The optimal filters that best characterize the input-output relationship between these IEGM and SECG templates are determined by means of adaptive filter technique. Specifically, the IEGM templates are extracted from the pacemaker sensing channels. Because the filter characteristics could be different for sensed and paces events, the IEGM templates should be representative of at least four different event types: atrial sense (AS), ventricular sense (VS), atrial pace (AP), and ventricular pace (VP). Correspondingly, the SECG templates are selected for representative sensed P wave, sensed QRS-T, paced P wave, and paced QRS-T from desired SECG lead. These SECG templates could be selected from a generic SECG database, or obtained from the same patient (subject-specific) if it is available.

In active filtering stage, the characterized filters process the IEGM signals to generate the pseudo-ECG, which is the conditional sum of the filtered atrial IEGM (AEGM) and the filtered ventricular IEGM (VEGM).

2.2. Template matching

Since the IEGM and SECG templates may come from different sources, they must be matched before the filter characterization stage, by following six steps:

1. Resample the SECG or IEGM template if necessary to ensure they have the same sampling frequency.
2. Adjust the baseline of SECG and IEGM templates if necessary to remove the DC offset.
3. Remove the pacing artifacts (manual editing or automatic removal) from the templates if necessary.
4. Identify the fiducial points of the templates (for SECG template, its peak is chosen as the fiducial point,

regardless of pacing or sensing. For paced IEGM, the device-generated pace marker identifies the fiducial point, while the nearest peak following the device sense marker is chosen as the fiducial point).
5. For sensed event, the SECG fiducial point is aligned with corresponding IEGM fiducial point with a proper delay (default 30 ms) to account for volume conduction between IEGM and SECG. For paced event, an additional delay (default 20 ms) is added in order to compensate for the interval from pace marker to the peak of evoked potential in IEGM. Optionally, if T wave can be identified in both SECG and VEGM templates, their peaks are also aligned with proper delay (default 30 ms).
6. After alignment of the fiducial points, the IEGM and SECG templates are adjusted to the same length, by pre-padding and/or post-padding. If the T waves are also aligned, then segment of the SECG template (100 ms after R peak to 30 ms before T peak) is re-sampled to match the segment length of the IEGM template.

2.3. Filter characterization

The normalized least mean square (NLMS) method is used to characterize the optimal filters relating the IEGM and SECG [5]. Four sets of filters are independently characterized based on event types (AS, VS, AP, VP).

Figure 1 shows the block diagram of the NLMS algorithm. The input signal IEGM (x_n) and the output signal SECG (d_n) are assumed to be related by a time-varying transfer function *H(n)*. The NLMS method aims to model *H(n)* using another filter *W(n)*, so that when given the same input (x_n), its output (y_n) best resembles the desired output (d_n). That is, the NLMS method adaptively adjusts the coefficients of *W(n)*, so that the error term (e_n=d_n-y_n) is minimized. The adaptation process can be described by the following equations:

$$y_n = W'(n-1) \cdot x_n \quad (1)$$

$$e_n = d_n - y_n \quad (2)$$

$$W(n) = \alpha \cdot W(n-1) + \mu \cdot \frac{e_n \cdot x_n}{\varepsilon + x_n' \cdot x_n} \quad (3)$$

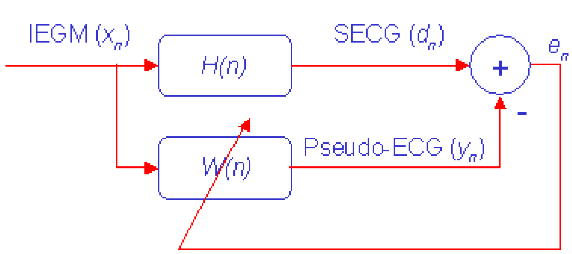

Figure 1. Block diagram of the NLMS algorithm

Here, α is the leakage factor ranging from 0 to 1, μ is the adaptation step size ranging from 0 to 2, ε is a small positive bias term that is used to improve the stability of the adaptation process. In this study, we fixed μ = 1.0 and ε = 1e-10. For both atrial and ventricular channels, the filter length is set to 32 for sampling rate of 512 Hz.

For a stationary signal, the adapted NLMS filter is generally time-invariant. However, for a non-stationary cardiac signal, the adapted filters still vary from sample to sample, particularly during the signal complexes. Therefore, it is necessary to apply sample-wise filters with proper segment length to the IEGM. That is, at least during the segment following the IEGM fiducial point, each sample is processed with a sample-specific filter. In this study, the segment length is set to 100 ms for atrial filters and 400 ms for ventricle filters, respectively.

After characterization, the adapted sample-wise filters are applied to the same IEGM template, and its output is compared with the SECG template to assess their similarity by measuring their correlation coefficient (*CC*):

$$CC = (y-\bar{y})^T (d-\bar{d}) / \|y\| \cdot \|d\| \quad (4)$$

Here, *y* and *d* respectively represent the vector of filtered IEGM template and desired SECG template, with respective mean values of $\bar{y}$ and $\bar{d}$. For a pair of IEGM and SECG templates, the optimal filters are defined as those leading to the maximal *CC*. The optimal α is found by looping through 0-1 with step size 0.05, and searching for the maximal *CC*. In addition, the ratio between peak amplitudes of *y* and *d* is used to determine the gain factor during active filtering stage, so that the peak amplitude of the pseudo-ECG is similar to that of the SECG template.

2.4. Active filtering

The AEGM and VEGM are respectively filtered (with previously characterized optimal filters), gained (with previously determined gain factors), and conditionally summed to generate the pseudo-ECG. Specifically:

- Starting from the fiducial point following an AS (or VS) event and within the predefined segment, the pseudo-ECG is the sum of the AEGM (or VEGM) processed by the sample-wise AS (or VS) filters, and the VEGM (or AEGM) processed by the first VS (or AS) filter corresponding to the fiducial point.

- Following an AP (or VP) marker and within the predefined segment, the pseudo-ECG is generated solely by the AEGM (or VEGM) processed by the sample-wise AP (or VP) filters, i.e., excluding the ventricle (or atrial) component. Besides, a predefined AP (or VP) template is copied to the output to represent the pacing artifact.

- For samples outside the predefined segment following a previous fiducial point, the pseudo-ECG is the sum of the AEGM processed by the first AS filter (for AS fiducial point), and the VEGM processed by the first VS filter (for VS fiducial point).

2.5. Experimental data

An anaesthetized pig was implanted with a right atrial lead and a right ventricular lead, both connected to a Stratos DR pacemaker (Biotronik, Berlin, Germany). By programming the device, various rhythms (AS-VS, AS-VP, AP-VS, AP-VP) were induced. The pacemaker recorded AEGM and VEGM (in both channels, ring electrode as cathode and pacemaker case as anode) with sampling frequency of 512 Hz, as well as the event markers. Meanwhile, a Propaq monitor (Welch Allyn, Oregon) was used to record (asynchronously to IEGM) the lead II SECG with sampling frequency of 181 Hz.

In addition, selected data from the Ann Arbor Electrogram Libraries (AAEL) containing arrhythmic episodes of dual-channel IEGM and SECG were tested.

3. Results

In the acute animal study, the pacemaker recorded IEGM that include 70 AS-VS cycles, 392 AS-VP cycles, 472 AP-VS cycles, and 431 AP-VP cycles. Optimal filters for AS, VS, AP, and VP events were characterized by selecting representative SECG and IEGM segments recorded from the pig. Pseudo-ECG was obtained by applying these filters to the IEGM, and then compared to the measured SECG (manually aligned to the IEGM due to asynchronous recording). For all cycles, the generated pseudo-ECG morphology is highly comparable to that of the measured SECG.

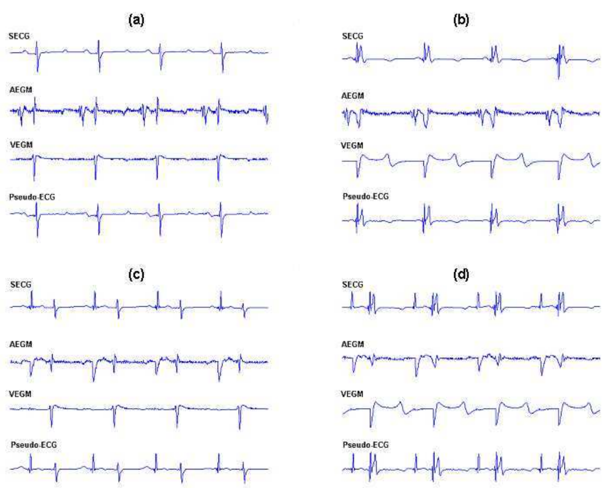

Figure 2. Examples of synthesizing pseudo-ECG in a swine model for both of sensed and paced rhythms.

Figure 2 shows typical examples of pseudo-ECG in different rhythms (4 cycles each): (a) AS-VS, (b) AS-VP, (c) AP-VS, (d) AP-VP. Note in this figure: (1) Due to ring-case sensing, each ventricular depolarization in VEGM (sensed or paced) is associated with a far-field projection in the AEGM; (2) The pacing artefacts were absent from both AEGM and VEGM due to pace blanking of the pacemaker; and (3) The pseudo-ECG has identical pace spike (copy of the VP pulse template), whereas the pace artefacts in SECG are inconsistent due to limited sampling rate (181 Hz). As evidenced in Figure 2, compared with the measured SECG, the pseudo-ECG shows distinct P-QRS-T waves whose morphology closely resembles those of the measured SECG.

Pseudo-ECG was also synthesized for selected AAEL episodes representing abnormal rhythms. For illustration purpose, Figure 3 shows four examples of pseudo-ECG corresponding to (a) atrial flutter (AAEL181), (b) atrial fibrillation (AAEL182), (c) ventricle flutter (AAEL177), and (d) ventricle fibrillation (AAEL197). Note in these examples, the SECG template was a generic one chosen from a patient in normal sinus rhythm (AAEL175). As expected, the morphology of pseudo-ECG does not match the measured SECG (lead I), but resembles that of the generic SECG template. Nonetheless, in all tested cases, clinically relevant cardiac rhythm information that is sufficient for diagnosis of the underlying rhythm is well preserved in the pseudo-ECG.

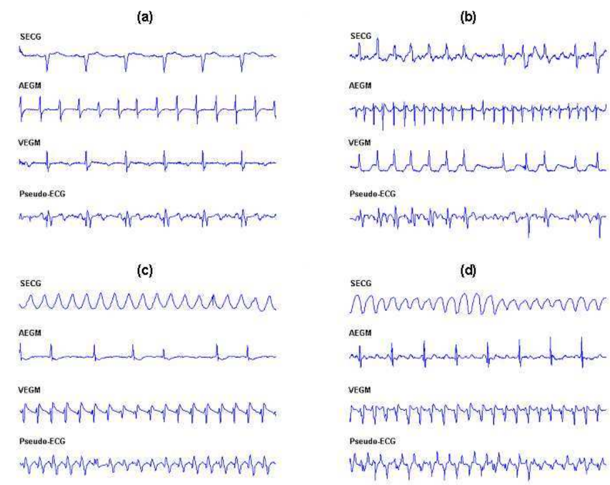

Figure 3. Examples of synthesizing pseudo-ECG in selected AAEL data files representing abnormal rhythms.

4. Discussion and conclusions

In this study, we proposed an algorithm to estimate the pseudo-ECG from the IEGM recorded by the implantable pacemaker. The adaptive filter method is used to characterize the optimal filters relating the representative IEGM templates and the desired SECG templates. The algorithm was preliminarily evaluated on experimental data collected from an acute animal study and in selected data from the AAEL. Promising results were obtained, demonstrating the feasibility of pseudo-ECG.

Previous approaches on pseudo-ECG had various disadvantages. Synthesizing pseudo-ECG by means of subcutaneous electrodes [1] requires special design, fabrication, and manufacture of the electrodes and the associated circuits, which add to the hardware complexity. So far, the only pseudo-ECG feature implemented in implant devices is based on far-field IEGM recorded with coil-case sense configuration, but the produced pseudo-ECG morphology is usually quite different than the measured SECG [2,3]. Another approach is to post-process the IEGM through filters which are trained using neural network or fuzzy logic [4]. However, the filters trained using one dataset may not be suitable to another dataset.

Theoretically, the IEGM can be considered as the near-field representation of the heart electrical activations, whereas the SECG is the far-field projection of the same cardiac signals. Any filter-based pseudo-ECG approach assumes that some linear or non-linear filters could relate the SECG and IEGM. However, it is important to realize that no fixed filter(s) could universally characterize the input-output relationship between IEGM and SECG, due to the variability in each of the three components of the system: (1) output: the SECG characteristics depend on the location of the surface lead, evidenced by different morphologies of the 12-lead SECG; (2) transfer function: the volume conductor characteristics vary from patient to patient due to difference in gender, age, torso geometry, etc.; and (3) input: the IEGM characteristics not only have inter-subject variability, but also have intra-subject variability (e.g., the IEGM morphology depends on the location and sensing properties of the pacemaker lead).

Therefore, the adaptive filter method is preferred for pseudo-ECG by designing optimal filters for individual subject (fixed volume conductor) with stable IEGM sensing channels (fixed input) and desired SECG lead (fixed output). As described above, the optimal filters are event-specific. The filter characteristics not only differ between atrial and ventricle channels (reflecting different volume conduction paths), but also differ between sensed and paced events (reflecting different IEGM properties). Moreover, the optimal filters for each event type (AS, VS, AP, VP) contain a bank of filters, whose characteristics vary from sample to sample, to account for the non-stationary properties of the cardiac signals.

This study has several limitations. First, quantitative analysis of the results was deferred due to asynchronous recording of the IEGM and SECG. Second, the algorithm requires identification of the fiducial points associated with the event markers. If the location of fiducial point is not consistent or the event markers are not available (e.g., device under-sensing), then the pseudo-ECG morphology may be distorted. Third, the optimal filters characterized for normal events may be sub-optimal for abnormal rhythms with different IEGM morphology, such as fusion beats, ectopic beats, flutter or fibrillation rhythms, etc. Furthermore, more rigorous evaluation of the algorithm in a larger database with more complex cardiac rhythms is warranted in the future study.

Finally, it is important to emphasize that the pseudo-ECG is not intended to replace the SECG, which can reveal subtle features (e.g., ST elevation) that may not be apparent in the pseudo-ECG. Instead, an immediate goal of pseudo-ECG is to simplify the pacemaker follow-up by providing ECG-like signal without the need of attaching skin electrode to the patient. Yet in a further application, the pseudo-ECG may support wired or wireless monitoring of implant device and cardiac function, by providing pseudo-ECG with reasonable morphology and cardiac rhythm information. Coupled with the recently developed Home Monitoring ™ technique [6,7], such ECG-online feature will ultimately bring it to reality for the remote device follow-up, reduce the medical cost and improve the quality of health care.

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