Analysis of Signal-Averaged Electrocardiogram Performance for Body Surface Recordings

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Abstract

To test the performance of signal averaging on body surface electrocardiograms (SAECG), a comparative analysis of four sources of perturbation, 1) uncorrelated noise, 2) beat alignment, 3) physiological variability and 4) respiratory movement was performed. The first two cases were assessed using a computer model of a ventricular beat. The other two cases were tested using high resolution body surface signals recorded from a torso tank (N=2) and patient data (N=4) respectively. In the first case, SAECG successfully removed a high level of noise made up of white Gaussian noise (WGN) with $\sigma = 10\ \mu V$ and 50 Hz noise with a signal to noise ratio (SNR) of 9 dB since the root mean square error of the noise ($RMSE_{noise}$) was $0.65 \pm 0.01\ \mu V$ and $1.30 \pm 0.01\ \mu V$, respectively. The RMSE of the averaged QRS ($RMSE_{SAQRS}$) was slightly changed by physiological variability ($RMSE_{SAQRS} = 4.18 \pm 1.38\ \mu V$) when comparing the SA_{QRS} resulting from the average of 100 different beats taken from the same recording. While SA_{QRS} are distorted by respiration artefacts, the beats selected during the exhalation phase produced the least distortion to the SA_{QRS} with a $RMSE_{SAQRS} = 16.28 \pm 12.58\ \mu V$. To conclude, SAECG can efficiently de-noise signals in presence of uncorrelated noise without distorting the SA_{QRS}. However, respiration motion introduces amplitude shift between SA_{QRS}.

1. Introduction

Signal averaging of an ECG (SAECG) is a non-invasive technique to reduce noise or increase the signal to noise ratio (SNR) without the distorting effects of filtering on the QRS [1]. This technique is mostly used in the detection of low amplitude signals called "late potentials" [2], [3], [4], markers for sustained ventricular arrhythmias embedded in the QRS but usually hidden by skeletal muscle activity and by external noise localized at the end of the QRS. The SAECG is also used to evaluate the risk for atrial fibrillation focusing on prolonged P wave [5] and for non-invasive electrocardiographic imaging [6].

Another potential application is the detection of His bundle activation from body surface signals [7]. However the very small potential associated to the His bundle activity combined with residual noise make this detection very challenging.

A high efficiency of SAECG to de-noise electrocardiograms (ECG) is imperative to identify low amplitude variations of ECG in part responsible for some arrhythmias. In this study, we aim to report the performance of SAECG in terms of noise reduction and SA_{QRS} modification testing various sources of signal perturbation, with the goal of setting an optimal workflow for future studies.

2. Materials and methods

2.1. Datasets

Three datasets were used to accomplish this study.
(i) A computer model (N=1) from a torso model with 252 body surface recordings at 1000Hz [8] composed of a ventricular beat duplicated into multiple beats equally spaced (RR interval = 909 ms (66 bpm)) or randomly spaced (RR interval =800 +/- 59 ms (75 bpm)). (ii) 5-minutes of experimental data (N=2, sinus rhythm and left ventricular pacing) obtained from a torso tank with 256 surface signals recorded at 2048 Hz simultaneously with 108 epicardial signals from a pig heart suspended inside and (iii) clinical data (N=4) composed of 128 body surface signals and breathing signal recorded simultaneously from a respiratory belt at 2048 Hz were used.

2.2. Comparisons methods

The efficacy of SAECG was assessed using 3 metrics:

1- the RMSE of noise ($RMSE_{noise}$) based on the average of the squared differences between a signal without noise ($RMSE_{noise} = 0$) and the noise measured over an interval of 50 ms during the ST segment;

2- the RMSE of the SA_{QRS} ($RMSE_{SAQRS}$) that measures the root mean square error between the "SA_{QRS} gold standard" and the SA_{QRS} obtained after SAECG. The "SA_{QRS} gold standard" chosen is detailed for each case in Section 2.3;

3- the correlation coefficient of the SA_{QRS} ($CorrCoeff_{SAQRS}$) calculated between the "SA_{QRS} gold standard" and the SA_{QRS} obtained after SAECG.

The results presented for these 3 metrics were computed from beat averaging for all the recorded leads. The mean of all the averaged leads was computed (252 channels for the computing model, 256 channels, for the experimental data, and 128 channels for the clinical data) and then the mean over the N sets of data available was calculated. For the experimental data N=2, for the clinical data N=4 and for the computer model N=15 as 15 random choices of 200 consecutives beats were used to compute the mean. Variables were reported as mean±SD.

2.3. Methods

The first step of SAECG was the creation of a virtual lead and a virtual template used for beat detection and alignment using a principal component analysis (PCA) [9]. PCA is a dimension-reduction technique used to reduce a large set of correlated variables to a smaller set of linearly uncorrelated variables called principal components. The first principal component contains the largest variance and was used in this study. The virtual template is compared with each beat of the virtual lead, by cross correlation. The positions for the alignment were determined as the position where the cross correlation was maximal. Finally beat averaging was performed over all recorded and aligned beats for each lead. Each case was processed using SAECG with or without signal processing tools (notch filter, band pass filter (BPF), baseline removal) to finally compute the three metrics presented in Section 2.2 (Figure 1). Signal processing algorithms were developed using Matlab (2015Rb).

Four sources of perturbation were analyzed to study the performance of SAECG.

Case 1: additive noise

To study the efficiency of SAECG to remove noise, a WGN ($\sigma = 10$ µV) was added to the simulated data (RR interval constant) and independently a 50 Hz noise with a SNR of 9 dB was added (RR interval non constant). For the latter, the use and performance of a notch filter was analyzed. The alignment was perfect as the known positions of each ventricular beat was used for averaging.

The $RMSE_{SAQRS}$ and the $CorrCoeff_{SAQRS}$ were computed between the SA_{QRS} (gold standard) without any noise.
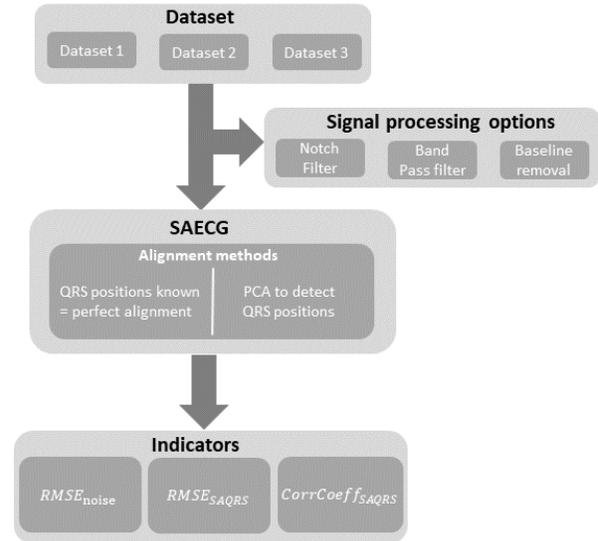

Figure 1: Workflow to test the SAECG performance. For each dataset signal processing methods can be applied independently, combined with each other or not used. Then SAECG is performed for each dataset using perfect alignment for case 1 and case 3 while QRS detection and alignment are determined with PCA method for case 2 and case 4. Finally, the three metrics can be computed.

Case 2: alignment perturbation

To study the effect of a bad alignment on the SA_{QRS}, a 50 Hz noise with a SNR of 9 dB, a WGN ($\sigma = 30$ µV) and baseline noise (created by fitting a spline to a patient dataset) were added to the simulated data (RR interval non constant). The use and performance of a notch filter and a BPF at 0.01 Hz to 30 Hz were compared. The $RMSE_{SAQRS}$ and the $CorrCoeff_{SAQRS}$ were computed between the SA_{QRS} obtained from dataset 1 after adding the different noises exposed previously 1) based on the average of perfectly aligned beats (SA_{QRS} gold standard) and 2) the SA_{QRS} based on PCA to set the positions of the beats (SA_{QRS} observed).

Case 3: physiologic variability

To study the impact of physiological variability on the SA_{QRS} using the experimental data, electrograms from a sock, because of the sharper QRS complex recorded, were used to set the QRS positions and to avoid any misalignment. To eliminate noise a notch filter with a band frequency of 1 Hz and baseline removal were applied. SA_{QRS} from five subsequences (100 beats each) of recording from dataset 2 were compared with each other (10 comparisons in total) to evaluate the variability of the SA_{QRS} as explained in Figure 2.
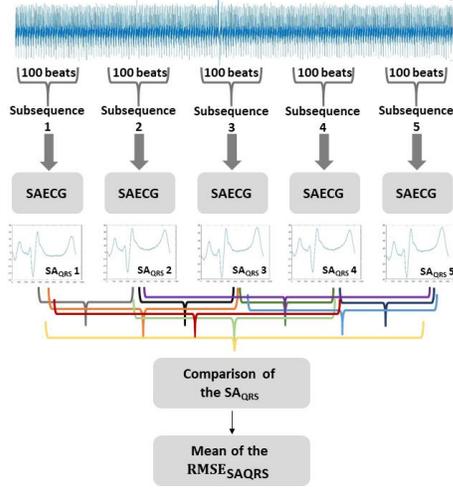
Figure 2: Workflow to compute the $RMSE_{SAQRS}$ for the physiological variability and the respiration motion study (for the latter case only three comparisons were performed).

Case 4: respiratory artefacts

To study the impact of respiration on the SA_{QRS} using the clinical data, three scenarios were compared: 1) only the beats in the exhalation respiratory phase were averaged, 2) only the beats during the inhalation respiratory phase were averaged, and 3) all the beats were averaged independently of the respiration. Baseline removal was used as a processing step. Three SA_{QRS} made from the average of 100 beats each along the same recording were compared with each other (3 comparisons in total) to evaluate the variability of the SA_{QRS}.

3. Results

Case 1: additive noise

Adding a WGN with σ =10 µV to the recording shows that after SAECG, $RMSE_{noise}$ decreases as expected in $\frac{\sigma}{\sqrt{N_{beats}}}$ since $RMSE_{noise}$=0.65+0.01 µV with a number of averaged beats equals to 200. In the presence of a 50 Hz noise (SNR = 9 dB) the use of a notch filter with a band frequency (BF) of 1 Hz reduced highly the noise in the signal ($RMSE_{noise}$=1.30±0.01 µV with notch filter vs 2.40±1.70 µV without notch filter), with a minimal distortion of the SA_{QRS} in terms of amplitude though the difference without notch filter was around half the $RMSE_{SAQRS}$ value while using a notch filter ($RMSE_{SAQRS}$ =1.43±0.00 µV with notch filter vs 2.30±1.67 µV without notch filter).

Our results also demonstrated that it is better to use a notch filter when the SNR of a 50 Hz noise is lower than 19 dB. However with higher SNR, the use of a notch filter is not necessary. Moreover these results are valid for 200 averaged beats. To conclude, 50 Hz and WGN noises can easily be removed by SAECG.

Case 2: alignment perturbation

Using a BPF was better than a notch filter to reduce noise ($RMSE_{noise}$ = 1.41±0.01 µV vs 3.08±0.5 µV). While the $Coeff\_corr_{SAQRS}$ in both cases was equal to 1, the BPF led to a smaller $RMSE_{SAQRS}$ than the notch filter ($RMSE_{SAQRS}$ = 0.51±0.20 µV vs $RMSE_{SAQRS}$ = 2.15±1.00 µV). As the levels of noise in case 1 (beat alignment is perfect) and case 2 are about the same range, we can conclude that potential misalignment was corrected through the use of filters (notch filter, BPF) and SAECG.

	$RMSE_{noise}$ (µV)		$RMSE_{QRS}$ (µV)		$CorrCoeff_{QRS}$	
	Before SAECG	SA_{QRS}	Before SAECG	SA_{QRS}	Before SAECG	SA_{QRS}
WGN (σ=10 µV)	9.23 ±0.06	0.65 ±0.01	9.99 ±0.2	0.71 ±0.00	0.99 ±0.00	1.00 ±0.00
50HZ (SNR=9dB) no notch filter	56.24 ±12.65	2.40 ±1.70	42.43 ±0.01	2.30 ±1.67	0.94 ±0.00	1.00 ±0.00
50HZ (SNR=9dB, notch filter BF = 1)	16.21 ±6.49	1.30 ±0.01	2.87 ±0.29	1.43 ±0.00	1.00 ±0.00	1.00 ±0.00
WGN + 50HZ + BL (notch filter BF =1)	38.21 ±8.07	3.08 ±0.5	40.73 ±8.44	2.15 ±1.00	0.93 ±0.00	1.00 ±0.00
WGN + 50HZ + BL (BPF [0.01 30] Hz)	9.03 ±0.30	1.41 ±0.01	12.66 ±1.35	0.51 ±0.20	0.96 ±0.00	1.00 ±0.00
Physiologic variability	6.84 ±1.23	1.30 ±0.68	12.89 ±2.94	4.18 ±1.38	0.87 ±0.03	0.98 ±0.01
Exhalation respiratory phase	6.85 ±2.95	1.88 ±1.23	38.59 ±16.00	16.28 ±12.58	0.95 ±0.06	0.99 ±0.01
Inhalation respiratory phase	6.89 ±2.70	1.95 ±1.25	60.12 ±51.14	18.69 ±14.60	0.93 ±0.04	0.99 ±0.01
No phase selected	7.70 ±3.10	1.97 ±1.20	47.27 ±23.88	19.21 ±16.54	0.94 ±0.06	0.99 ±0.01

Table 1: Table summary of the results

CASE 1	CASE 2	CASE 3	CASE 4

BF = Band Frequency   BPF = Band Pass filter   WGN = White Gaussian Noise
BL = Baseline   SNR = Signal to Noise Ratio

Case 3: physiological variability

Physiological variability has a poor effect on the SA_{QRS} correlation coefficient ($CorrCoeff_{SAQRS}$= 0.98±0.01) and a minimal impact on the $RMSE_{SAQRS}$ ($RMSE_{SAQRS}$= 4.18±1.38 mV) while averaging 100 beats.

Case 4: respiratory artefacts

SAECG in different phases of respiration demonstrated that selecting the beats during the exhalation phase produced the least change in the QRS waveforms amplitude (Figure 3A) when compared to the inhalation phase (B) or without any preliminary selection of the beats

(C). This is quantified by an $RMSE_{SAQRS}$ of 16.28±12.58 µV compared to $RMSE_{SAQRS}$= 18.69±14.60 µV and $RMSE_{SAQRS}$= 19.21±16.54 µV respectively. However, the correlation coefficient ($CorrCoeff_{SAQRS}$= 0.99±0.1) was similar for the three scenarios indicating there is minimal deformation of the QRS waveform.
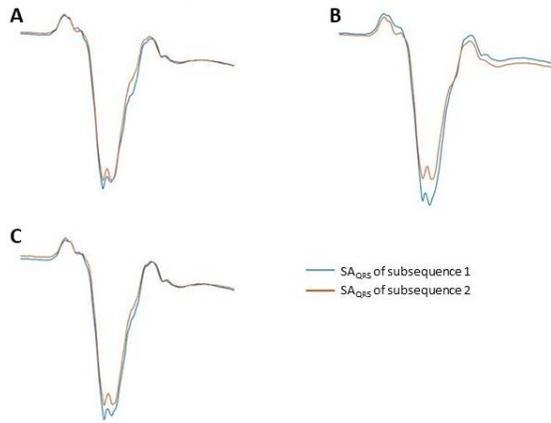

Figure 3: Comparison between two SA_{QRS} from two subsequences (100 beats averaged) within the same recording from dataset 3.
- A. SA_{QRS} selected during the exhalation respiratory.
- B. SA_{QRS} selected during the inhalation respiratory.
- C. SA_{QRS} with no preliminary selection of the beats.

4.   Discussion

The presented results demonstrate that SAECG is a performant technique to remove uncorrelated noise and to reveal the true underlying QRS complex. These results are consistent with previous studies showing the efficiency of SAECG, especially to detect small electrical components as the late potentials.

While the present study has supplied much useful information about the efficiency of SAECG, it has several limitations that must be acknowledged. Firstly, the results of this study could be more accurate using larger and longer experimental and clinical datasets. Finally, the correlation coefficient of the SA_{QRS} was computed on the entire SA_{QRS} complex leading to correlation coefficient superior to 0.9 in most cases. However, when using SAECG to detect late potentials for instance a very small distortion of the QRS can affect their detection but will not deteriorate the correlation coefficient much. Therefore, the results of this study would have to be interpreted according to each specific application.

5.   Conclusion

SAECG is a powerful signal processing technique to denoise the ECG without distorting the signals. 50 Hz noise, WGN and baseline artefacts while using SAECG (coupling to certain filtering process in some cases) are easily removed and SA_{QRS} distortion is minimal. Physiological variability has a weak impact on the SA_{QRS} distortion with SA_{QRS} using different beats within the same recording showing only very small deformations. On the other hand, the respiratory motion can deteriorate the SA_{QRS}, but by selecting the beats during the exhalation phase the amplitude shift effects of the SA_{QRS} can be reduced.

Acknowledgments

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