

Optimising Beat Selection and Averaging for ECGI to Enhance EGM Reconstruction Fidelity

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Abstract

Electrocardiographic Imaging (ECGI) offers spatially resolved information on cardiac electrophysiology by solving an inverse problem. By strategically placing electrodes on the torso, ECGI captures body surface potentials (BSP) to reconstruct the underlying electrical activity as electrograms (EGM) on the epicardial surface. Single-beat BSP are typically used to solve the inverse problem. However, the presence of noise and artifacts within the chosen beat can significantly distort the reconstructed EGM.

This paper introduces a novel approach to mitigate the impact of noise and artifacts on ECGI solutions by generating single averaged BSP beats. Our approach automatically identifies BSP segments with minimum RR-variability and selects consecutive artifact-free beats using entropy-based criteria. We compare the proposed approach with alternatives and our results demonstrate the efficacy of this approach in reducing amplitude variability across selected beats before averaging, thereby enhancing the fidelity of reconstructed EGMs. Furthermore, our study establishes the optimal number of beats required during averaging. Specifically, we found that at least 10 beats are needed to compute ventricular repolarisation time, and 50 beats for atrial repolarisation time. The proposed method offers a more efficient, reliable, and objective approach alternative to manual beat selection in ECGI.

1. Introduction

Electrocardiographic Imaging (ECGI) uses inverse problem approaches to reconstruct the electrical activity on the surface of the heart from high density Body Surface Potentials (BSP). The reconstruction utilises patient-specific heart-torso geometry to solve the formulated inverse problem [1].

Traditionally, ECGI relies on selecting individual beats

from BSP recordings for solving the underlying inverse problem. However, the accuracy and reliability of the reconstructed electrograms (EGMs) are highly sensitive to noise and artifacts present in the BSP signals [2]. To address this, beat selection is often done manually by visually inspecting the BSP recordings and choosing the least noisy beat. In this paper, we present an automatic approach to select and average BSP beats to produce a single beat which minimises the noise and artifacts in the ECGI solution.

2. Materials and Methods

2.1. Data

For validating the proposed approach we chose data from five healthy participants from a study of bariatric surgery [3]. The collected data consists of 10-minute BSP recordings from 256 electrodes. BSP were recorded at a sampling rate of 2048 Hz. Participant-specific heart-torso geometries were generated from MRI scans that included markers identifying the electrode locations.

2.2. Preprocessing of BSP

Before selecting and averaging the beats, BSP were pre-processed as follows. First, we applied a Savitzky-Golay filter with window length 2049 and polynomial order 2 to extract and then to subtract the BSP baseline. After removing the baseline, powerline interference (50 Hz) was removed using a notch filter and finally, a 5th order Butterworth lowpass filter with cut-off frequency of 150 Hz was applied, as per The American Heart Association guidelines.

2.3. Segment Selection

To identify stable beats for averaging, we first select a short BSP segment from the available 10 minutes con-

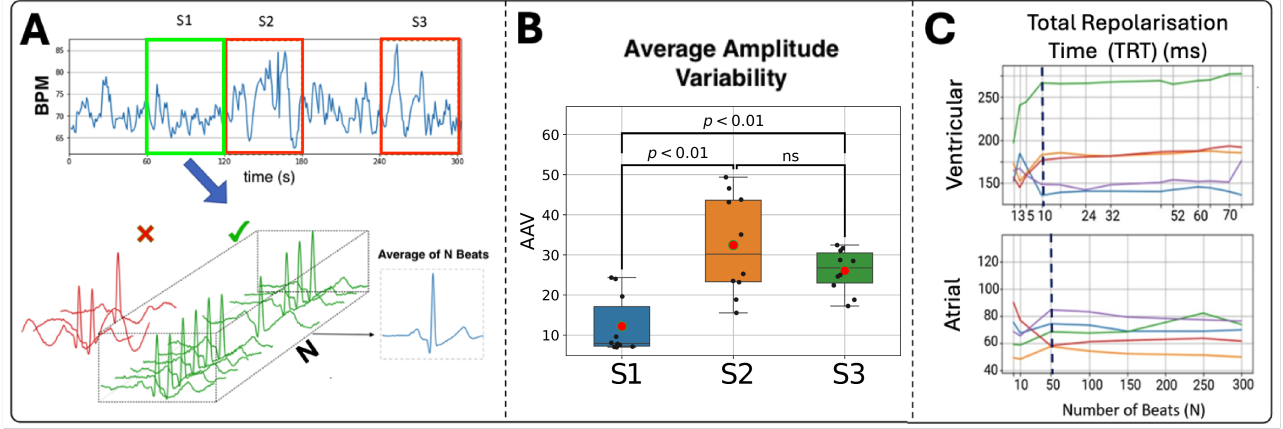


Figure 1. Figure: (A) Segment selection from BSP, rejection of artifactual beats, and averaging of N beats. (B) Average Amplitude Variability of three segments (C) Total Repolarisation Time (TRT) of Ventricles and Atria with different number of beats to establish the minimum number of beats.

taining beats with similar morphology. In our proposed method, a segment with stable beats is considered to be more effective, and its stability is measured using RR variability. The segment duration is determined by the number of beats to be averaged. For example, a 1-minute segment (approximately 60 beats) is sufficient to average 10 beats, considering the beat rejection.

Out of the 256 electrodes, recordings from those placed on the back of the torso tend to be less noisy, due to better skin contact with the flat anatomy. After identifying the R-peaks from the electrodes on the back, we select a single electrode (channel) with the lowest R-peaks-to-artifact ratio, R_p , calculated as

$$R_p = \frac{N_B}{N_B + N_G} \quad (1)$$

where N_B is the number of bad (rejected) beats and N_G denotes the number of good (accepted) beats. The approach from [4] is used to detect R-peaks and compute R_p . From the selected electrode with lowest R_p , the heart rate $BPM(i)$ at each beat location is calculated as follows:

$$BPM(i) = \frac{60}{RRI(i)} \quad (2)$$

where $RRI(i) = t_i^r - t_{i-1}^r$, is the RR-interval in seconds at i^{th} beat and t_i^r is time of the i^{th} R-peak. An example is shown in Figure 1A, top panel.

2.4. Beat Rejection

After selecting a segment with minimal RR variability, artifactual and noisy beats are rejected based on power and spectral entropy criteria. For the power criterion, beats with unusually high power are excluded. Unusually high

power is defined as any value greater than $1.5 \times IQR + Q_3$, where IQR represents the interquartile range and Q_3 is the third quartile. However, beats with unusually low power $< 1.5 \times IQR - Q_1$, where Q_1 is the first quartile are not rejected, since some electrodes may exhibit very low amplitude depending on their alignment. The power of each beat is calculated as follows:

$$P_{beat} = \frac{1}{T} \sum_{t=0}^{T-1} |x(t)|^2, \quad (3)$$

where T is the length (in samples) of beat, $x(t)$. We use t as discrete variable of time.

Using the spectral entropy criterion, beats with unusually high or low spectral entropy are rejected. High spectral entropy suggests the presence of numerous frequency components (noise-like characteristics), while low spectral entropy indicates fewer frequency components. The spectral entropy of a beat is calculated as follows:

$$SE = - \sum_f p_x(f) \log_2(p_x(f)) \quad (4)$$

where $p_x(f)$ is power spectral density computed by Welch method, such that $\sum_f p_x(f) = 1$, which was obtained using software [5]. The method of beat rejection is illustrated in Figure 1A (bottom panel).

2.5. Averaging Beats

After rejecting noisy and artifactual beats across all electrode recordings from the selected segment, N consecutive beats are chosen and averaged along the time axis. Since beats are rejected across all electrodes, some channels may not have N usable beats. In such cases, the process is repeated by extending the duration of the selected segment.

Figure 1A illustrates the process of segment selection, beat rejection and beat averaging.

3. Results and Discussions

To evaluate the effectiveness of the proposed approach for selecting segment $S1$ and rejecting beats, two additional 1-minute segments, $S2$ and $S3$ were selected for comparison, as shown in Figure 1A.

3.1. Visual Inspection of Aligned Beats

The beats in segments $S1$, $S2$, and $S3$ were aligned with their respective R-peaks and presented as heatmaps in Figure 2. The left and right panels illustrate the aligned beats before and after applying the beat rejection method, respectively. To evaluate the effects of beat rejection independently, this approach was also applied to segments $S2$ and $S3$. From the figure, it is evident that the beats in segment $S1$ are relatively uniform in length compared to those in segments $S2$ and $S3$. The heatmap for segment $S1$ appears flatter on both sides, while segment $S2$ exhibits significant variability in beat length, consistent with the goal of minimising RR interval variability through the segment selection approach.

Additionally, Figure 2 indicates that beats in segments $S2$ and $S3$ are noisier and more artifactual, with less alignment of P-waves and T-waves compared to those in segment $S1$. This variation reflects differences in morphology. In contrast, most beats in segment $S1$ show consistent morphology, with well-aligned P-waves and T-waves. Although the majority of beats in $S1$ are similar, some artifactual beats with differing T-waves remain, which could affect the averaged beat if not removed.

The impact of the beat rejection approach is evident in the right panel of Figure 2. Following the power and spectral entropy criteria, most artifactual beats were eliminated from all three segments. However, because the rejection criteria rely heavily on the values within a segment, the beat rejection method is less effective for segments $S2$ and $S3$, which contain many beats of varying morphology.

In conclusion, the analysis of Figure 2 demonstrates that combining both beat rejection and segment selection yields better results than applying either method alone.

3.2. Average Amplitude Variability

To quantify the effects of segment selection and beat rejection, we define Average Amplitude Variability (AAV). AAV is calculated as the average standard deviation of amplitude across the time axis from N beats $x_i(t)$ aligned with R-peaks. The computation of AAV for averaging N beats from a segment is given by the following equations:

$$x_\mu(t) = \frac{1}{N} \sum_{i=0}^{N-1} x_i(t) \quad (5)$$

$$x_\sigma(t) = \left(\frac{1}{N} \sum_{i=0}^{N-1} (x_i(t) - x_\mu(t))^2 \right)^{1/2} \quad (6)$$

$$AAV_N = \frac{1}{T} \sum_{t=0}^{T-1} x_\sigma(t) \quad (7)$$

In above equations, $x_\mu(t)$ and $x_\sigma(t)$ are the average and standard deviation of N beats across time, respectively. $AAV_N \in \mathbf{R}$ is the average amplitude variability for N beats and T is length of a beat (number of samples).

A lower value of AAV_N indicates a higher degree of similarity among the selected N beats, while a higher value reflects greater morphological variability. As AAV is derived from standard deviation, it can also be interpreted as a measure of certainty regarding the averaged beat, essentially indicating how closely N beats cluster around the averaged beat $x_\mu(t)$.

To illustrate the utility of AAV, we plot $x_\mu(t)$ and $x_\mu(t) \pm x_\sigma(t)$ for 10 consecutive beats from segment $S1$ across three scenarios: (1) after beat rejection, (2) before beat rejection, and (3) for random 10 consecutive beats without beat rejection, as shown in Figure 3. The standard deviation $x_\sigma(t)$ across time is represented as a shaded region alongside averaged beat $x_\mu(t)$. From Figure 3, it is evident that the shaded region in the left panel is very narrow, indicating a high degree of similarity among the 10 beats. The middle panel shows greater variability, as expected, with a low standard deviation around the R-peak due to its resilience to noise and artifacts from high depolarisation intensity. However, the P-wave and T-wave exhibit greater noise susceptibility, evident in the thicker shaded region. The right panel indicates that selecting 10 consecutive beats from a random location within the segment does not yield the same level of consistency as shown in the left panel.

Next, we utilise AAV to assess the efficacy of the proposed approach. We consider the same three segments $S1$, $S2$, and $S3$ after applying beat rejection, as depicted in the right panel of Figure 2. We extract 10 consecutive beats randomly (rather than just the first 10) from each segment to compute AAV. For example, to select 10 consecutive beats at random location, we pick a random number between 1 and $M-10$ (total beats M) and then select 10 consecutive beats. This process is repeated across 10 trials for each segment to prepare three groups to compare.

Figure 1B shows the AAV of 10 trials for each segment $S1$, $S2$, and $S3$. Using the Wilcoxon Rank-Sum test to compare the means, we observe that average AAV for segment $S1$ is significantly ($p < 0.01$) less than segments

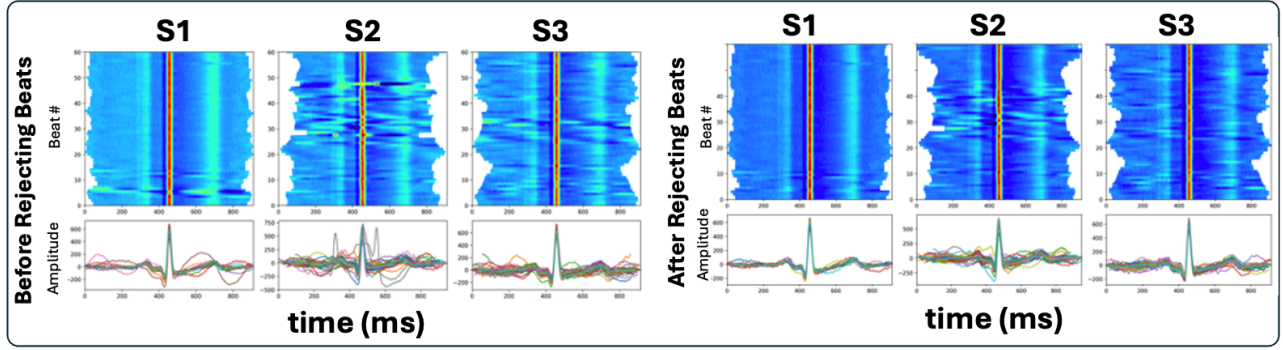


Figure 2. Aligned beats for comparing three segments before and after beat rejection.

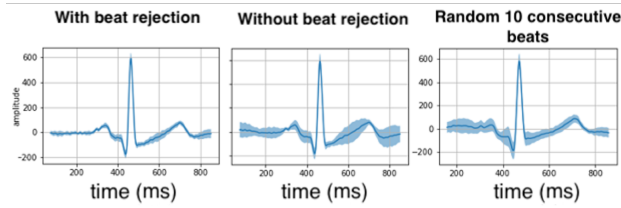


Figure 3. Average and standard deviation of 10 consecutive beats, across time axis.

$S2$ and $S3$, while average AAV of segments $S2$ and $S3$ are closer to each other. These statistical results strongly suggest that the combination of segment selection and beat rejection effectively reduces AAV.

3.3. Total Repolarisation Time (TRT) and Number of Beats

To determine the minimum number of beats required for ventricular and atrial analysis, we compared the Total Repolarisation Time (TRT) from reconstructed EGMs. The Local Repolarisation Time (RT) for each EGM was calculated using the Wyatt method, which identifies the time of the maximum up-slope of the T-wave for ventricles and the P-wave for atria. TRT was computed as 95 percentile range of repolarisation time, which has been proven to be more robust against noise in EGMs than using the full range. Ventricular and atrial TRT were analysed from the data of five participants by varying N , the number of beats averaged to produce single beat using proposed approach. The results are shown in Figure 1C. The figure shows that ventricular TRT stabilises after averaging 10 beats, while atrial TRT requires around 50 beats to reach stability. This difference is due to the higher noise levels present in P-waves in the reconstructed EGM for atrial analysis.

4. Conclusions

In this paper, we have introduced a novel method for automatically selecting and averaging beats across all electrodes of BSP to generate an averaged beat. Our approach involves selecting segments with minimal RR variability and rejecting beats based on power and entropy criteria, leading to a significant reduction in AAV. Additionally, we determine the minimum number of beats required for reliable ventricular and atrial TRT, which are 10 and 50 beats, respectively.

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