Impact of baseline drift removal on ECG beat classification and alignment

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Abstract

Accurate beat classification and alignment is fundamental to any signal averaging method. The objective of this study was to investigate the accuracy of different beat classification and alignment methods, and the impact of pre-processing methods on these algorithms.

Experimental data came from a human-shaped torso tank, with 256 body surface ECG recorded during sinus rhythm (SR) and left ventricular pacing (LVP) (n=4). "Gold-standard" classification and alignment were defined from recorded cardiac electrograms. Six different methods of baseline drift removal (BDR) were applied to ECG. Subsequently, 3 different beat segmentation methods were used to extract QRS complexes and align them, and four different beat classification methods.

Pre-processing methods had only a small impact on beat classification and alignment compared to the segmentation and classification methods themselves. However, baseline drift removal over the whole QRS does appears to be important in providing the most accurate final averaged beat.

1. Introduction

Signal averaging is a useful technique to reduce or eliminate noise without the potentially distorting effects of filtering on the signal waveform. Signal averaging has previously been used to filter body surface signals prior to application of non-invasive electrocardiographic imaging (ECGI) as a means to reduce high-frequency noise [1,2]. However, in our recent study evaluating the effects of different filtering methods on ECGI reconstructions, we found signal averaging was only beneficial in certain cases, and could actually be detrimental to the reconstruction compared to not filtering the signal at all [2]. We suspect these different results were due to beat alignment issues; that is detrimental results occurred when alignment was poor resulting in QRS deformation in the ECG.

We hypothesize that if the optimal signal averaging approach can be determined, it will provide the best filtering tool to use for ECGI with stable rhythms. As such the following study investigates the accuracy of different beat segmentation, alignment and classification methods. As this process may be improved or hindered by any signal pre-processing used, in particular by baseline drift removal, 6 different methods of baseline drift removal were also investigated.

2. Methods

2.1. Experimental Data

The experimental protocol used to obtain this data set has previously been described in [3]. An excised pig heart (35 kg) was perfused in Langendorff mode. An epicardial electrode sock (108 electrodes) was attached to the ventricles and bipolar pacing leads to the LV freewall. The heart was transferred to a human-shaped torso tank filled with an electrolytic solution (conductivity of 500 Ω-cm) and with 256 electrodes embedded in the surface. Tank and sock signals were recorded simultaneously (BioSemi, the Netherlands) for two 2-minute episodes of sinus rhythm and left ventricular (LV) pacing (n=4).

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2.2. Signal Processing Methods

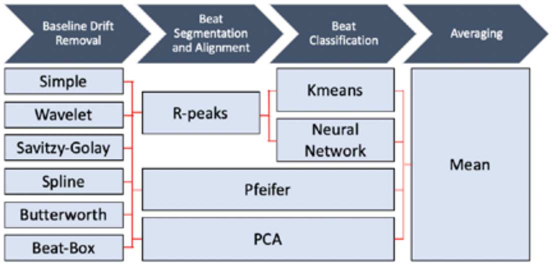

Fig 1. The four steps of signal processing for raw ECG.

Fig 1 outlines the four steps of signal processing used. First baseline drift was removed. A template "goal" QRS-complex was used to segment and align the beats. The segmented beats were then classified as "goal" or "not-goal" and finally the identified "goal" beats were averaged.

2.2.1 Step 1: Baseline Drift Removal

Six different methods of baseline drift removal (BDR) were applied:

1. *Simple:* A naive approach where the mean over a 20 ms window during the isoelectric period pre-QRS was subtracted from each beat.
2. *Wavelet-based:* A wavelet bandpass filter with the decomposition performed over 20 wavelets and the filtering within 0.5-150 Hz band.
3. *Savitzky-Golay:* A Savitzky-Golay FIR smoothing filter was applied to the data with a polynomial order of 3 and a frame length of 3000 ms.
4. *Spline-based:* A spline-based method using predefined expected isoelectric points for computation of the zero line by fitting the isoelectric line with a cubic function.
5. *Butterworth High Pass Filter:* IIR high pass filters with filter order 5 at cut-off frequency of 0.5 Hz.
6. *Beat-Box:* A moving average filter with a width the approximate cycle length to produce an estimate of the baseline that is subtracted from the raw recording.

2.2.2 Step 2: Segmentation and Alignment

Three different methods were used to segment all QRS complexes throughout the signal and align them with the template beat.

1. *R-peaks:* R-peaks were identified in a selected lead by Pan-Tompkins method and the beat using a window around the R-peak.
2. *PFEIFER:* A time-shift between the template and a the ECG signals was used. The lag corresponding to the peaks in cross-correlation (over select electrodes) was used to segment the beats, and determine alignment.
3. *PCA-based [4]:* Principal component analysis (PCA) was applied to the ECG and the first PC used to define the virtual lead and virtual template. The time-shift approach was used on the virtual signals.

2.2.3 Step 3: Beat Classification

For the Pfeifer and PCA methods, classification of the QRS complexes that corresponded to the "goal" template QRS was performed during segmentation, by identifying all beats with a cross-correlation above threshold as "goal" (threshold of 0.9 for the PCA method and 0.95 for Pfeifer). For beats aligned using the R-peaks method, classification was determined using two different methods:

4. K-means: Segmented beats were clustered to 10 clusters according to the criterion of the minimal L2 norm of the difference between the beats in the cluster.
5. Neural Network [5]: Finds clusters within data based on the principle of competitive learning. Each beat was classified into one of 10 clusters based on the similarity between this beat and the beats in that cluster.

2.2.4 Step 4: Averaging

Beat averaging was performed for each method using all beats identified by the classification algorithms as "goal", taking the mean as the average.

2.2. Evaluation Criteria

"Gold-standard" beats alignment was obtained by computing the AT maps for all beats, and aligning them using the minimum medium absolute error over all electrodes. "Gold standard" fiducials marking the start of each beat was extracted from this alignment and used to evaluate alignment error with the mean absolute error (ms).

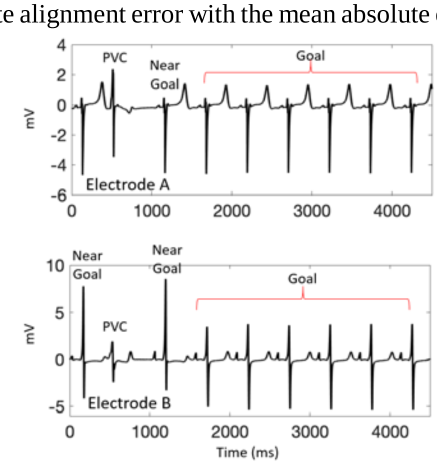

Fig 2. Example of 2 sock electrodes and the beats identified as "goal", "near goal" or "PVC".

"Gold-standard" beat classification were semi-automatically obtained from EGMs. Beats were classified as "goal" (the most common QRS seen), "near-goal" (close to goal but with regional differences in EGMs due to physiological variability) or "not-goal" (e.g. PVCs), as demonstrated in Fig. 2. Classification of beats as "goal" was evaluated using the sensitivity and specificity for each method.

To quantify the accuracy of averaged beats, the difference between the template beat and the final averaged beat was computed. From this residual, the signal-to-noise (SNR) ratio, to quantify any remaining QRS (a perfect averaged beat will results in pure noise in the residual and SNR of <1dB).

3. Results

The LVP and SR sequences were composed of a total 582 and 419 "goal", 5 and 8 "near-goal" and 7 and 15 "not-goal" QRS-complexes respectively.

3.1. Alignment

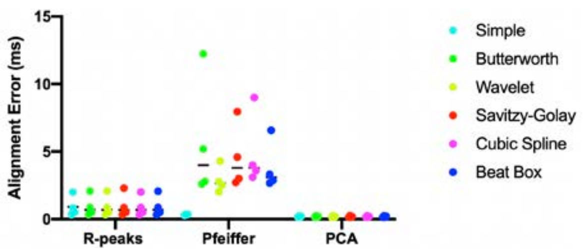

Fig. 3 presents the comparison in mean absolute alignment error (ms) between the different segmentation and baseline drift removal methods for each ECG recording.

Overall, the alignment of beats for most methods was good (<5 ms error; Fig 3). The biggest differences in accuracy came from the different segmentation method used ($p<0.01$), rather than the baseline removal method ($p=0.16$), with PCA producing a near perfect alignment (<0.5 ms) and the most consistent results for this data.

For Pfeifer, the baseline removal method had a large impact on alignment with the simple method providing the most accurate results similar to PCA ($p<0.0001$). This may be due to the other methods deforming the QRST and impacting alignment through correlation of these waveforms. For the PCA and R-peaks on the other-hand, baseline drift removal had no major impact on the alignment.

3.2. Classification

The PCA, K-means and Neural Network demonstrated an excellent sensitivity for all signals (>0.99, >0.96 and >0.95 respectively), with little difference between the baseline drift removal methods (Fig 4). Pfeifer had a good sensitivity for LV pacing signals (>0.96) for all baseline drift removal methods except the cubic spline. For sinus rhythm however, around 40% of the "goal" QRS complexes were not detected with Pfeifer.

For specificity on the other hand, only the PCA showed a relatively good ability to detect "not-goal" beats with values 0.8 for all signal types and little difference between baseline drift removal methods. Kmeans likewise performed well for both sinus rhythm and 1 of the 2 LV pacing signals except with simple baseline drift removal. The Neural Networks performed well for 1 sinus rhythm signal with little impact from baseline drift removal. Finally, Pfeifer performed the worst, with nearly all signals below 0.8 except for 1 sinus rhythm signal with simple or Butterworth baseline drift removal.

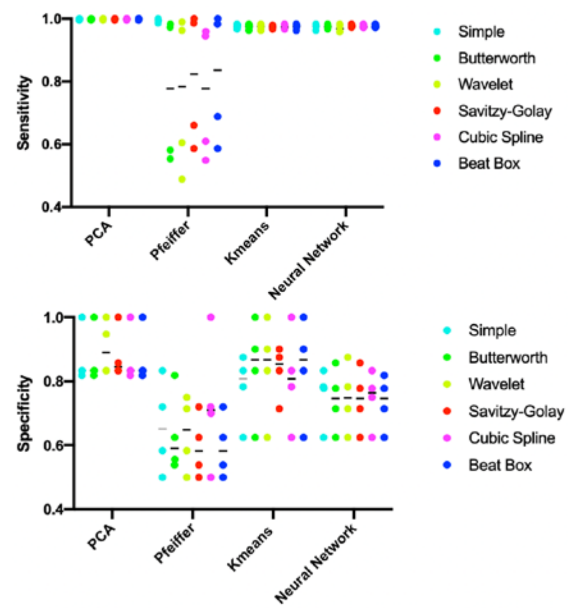

Fig. 4 presents the sensitivity and specificity for the detection of "goal" QRS complexes for the different classification and baseline drift removal methods for each ECG recording.

3.2. Averaging

An example for a single lead during sinus rhythm is presented in Fig 5 for each classification algorithm after baseline drift removal. The impact of alignment error can be seen in the Pfeifer aligned beats, as there is clearly some remaining QRS in the the residual for the Butterworth and Wavelet cases. It also appears that an alignment error under 4 ms coupled with a low number of false positive "goal" beats is sufficient to remove this remaining QRS from the signal, as is seen in the remaining examples the residual appears to be pure noise.

As expected, Pfeifer produced the highest SNR with

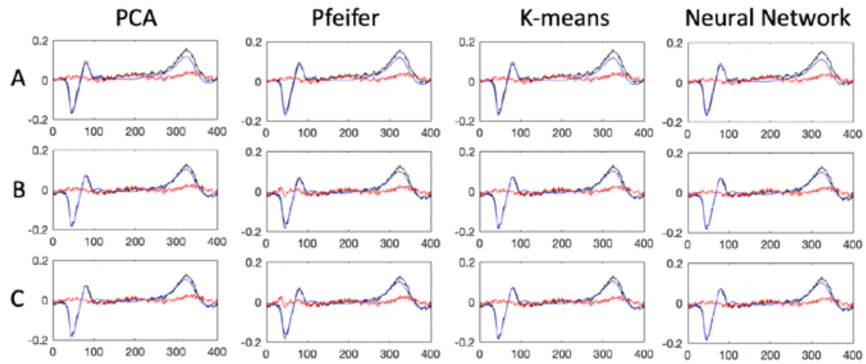

Fig 5. Examples of a single ECG in sinus rhythm for each classification algorithm (columns) after A) simple, B) butterworth and C) wavelet baseline drift removal. Each plot contains the template beat (black), the signal averaged beat (blue) and the difference (residual) between them (red).

both alignment and classification results worse than the other methods. Interestingly, despite having a poor specificity, the simple method of baseline drift removal produced one of the best SNR. This method also had a near perfect alignment (error <0.5 ms), indicating that including a small number of "non-goal" beats does not substantially impact the final QRS morphology.

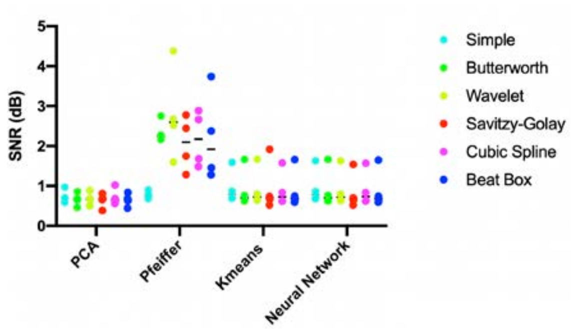

Fig 6 presents the signal-to-noise (SNR) ratio of the difference between the signal averaged and template beat.

The SNR for PCA, K-means and the Neural Network were similar for most signals despite differences in alignment error. This suggests 1 ms error is a good threshold to aim for in order to minimize the impact on the final QRS morphology. Furthermore for the PCA, although alignment error was the same for all baseline drift removal methods, there was a notable difference in the SNR they each produced suggesting baseline drift removal may alter the QRS waveform morphologies in some way. Interestingly, the simple method, which does not affect the QRS morphology, produced one of the highest SNR meaning it is important to remove baseline drift over the whole QRS, and not just reset the iso-electric line.

4. Conclusions

Pre-processing methods had only a small impact on beat classification and alignment compared to the methods of signal averaging themselves. The PCA produced the most accurate alignment and classification.

Evaluation of the residual between the final averaged beat and the template beat indicated that specificity of the beat classification was less important than beat alignment. However, this is likely only the case in this study where the number of "not-goal" beats that could be detected was very small (2.1-5.5% of the total beats). It was further found that an alignment error <1 ms was sufficient to reduce the SNR of the residual to within acceptable levels, and that is important to remove baseline drift over the whole QRS, and not just reset the iso-electric line to produce an accurate final averaged beat.

The results should be interpreted in light of the limitations. Namely, only a small data set from a single experimental set up was used. We are currently expanding our analysis to include more data sets, and use this data to perform ECGI and assess the impact on reconstructions.

Acknowledgments

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