Examination of the Poincaré map method for detecting T-Wave alterans

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***Abstract*—This report implements the Poincaré mapping method for detecting T-Wave alterans. It then uses the method to analyze ECG signals from three different subjects and evaluate its performance. The changes in performance when tweaking some parameters is also examined. It is found that there is no choice of parameters that work best for all signals, and tweaking for each individual subject is required. No significant difference is found between the cubic spline method of baseline wander cancellation and the moving median method for baseline wander cancellation when the ECG has a normal PQ segment. The Poincaré mapping method seems to be able to perform tracking of shorter TWA episodes compared to the similar spectral method but this implementation of the method has trouble identifying TWA in noisier data.**

I. Introduction

T-wave alterans (TWA) is an electrocardiographic phenomenon that is characterized by the T-Wave of every other heartbeat recording a higher or lower value. TWA has been shown to correlate with ventricular arrhythmia [1]. It is therefore useful to be able to identify TWA. The area of TWA detection has a lot of research behind it and there are several methods that have been shown to work in identifying it [2]. One of the more widely used methods is called the *Spectral Method* and works by transforming the signal into the frequency domain and looking at the energy at $0.5hz$ where one hertz is one heartbeat, a high energy would indicate that alterans is present [1]. A weakness of the model is that it calls for a sample size of upwards of 128 heartbeats so dynamic tracking is difficult. A method that tries to rectify this is the *Complex Demodulation Method*. This method models the signal as a sinusoidal signal with a period of two beats and takes a measure of the alterans by demodulating the 1hz component. This method can be done using less beats and is therefore capable of dynamic tracking of the alterans [1]. In this report, the *Poincaré Mapping Method* is implemented. The Poincaré mapping method is a variation on the Spectral Method that allows for dynamical tracking.

II. Data

The data analyzed is ECG taken from one human subject and two pigs in Lund, Sweden. All data is sampled using $1000hz$ and vary in length between 5 and 7 minutes. The human data has exceptionally large T waves and is collected by a single lead ECG during balloon dilation of an occluded artery of the heart. The pig data was collected using a 12-lead ECG during coronary artery occlusion.

III. Methods

According to [2] any TWA detection algorithm has three main components: *Preprocessing*, *Data reduction* and *TWA Analysis*.

A. Preprocessing

The first step in the preprocessing was to normalize the signal in order to produce a comparable index in the end. This was done by dividing the entire signal by the mean absolute value of the signal.

The second step was filtering. As suggested in [2] the signal was put through a notch filter at $50hz$ in order to remove the $50hz$ noise that can be produced by the alternating current with the same frequency that runs through the power oultets in Sweden, where the data was collected. The paper also suggests using a low pass filter. The signal was put through a low pass filter with cutoff $100hz$ to remove some of the high frequency noise in the signal.

In order to remove lower frequency noise (such as breathing) the signal was subjected to *Baseline Wander Cancellation*. Two different methods of baseline wander cancellation were tried. The first was the *Cubic Spline Method*. This method uses the point 66ms before the maximum slope in the Q complex as a baseline and uses cubic spline interpolation to create a continuous signal that can be subtracted from the signal [3]. This method assumes that there are no abnormalities in the PQ segment of the ECG [3]. The alternative method was the *Moving Median Method* described in [4]. This method subtracts a moving median of the signal from the signal. Instead of using two windows like in [4] a single window of the size of three heartbeats was used as to not remove any information about TWA.

The first 10 and the last 10 beats were then thrown out as they were corrupted by the preprocessing.

B. Data reduction

The data was decimated after identifying the ST-T complex simply by downsampling to seven points along the ST-T complex like in [5].

C. TWA Analysis

A Poincaré Map is a map on a periodic or semi-periodic function $x(t)$ that maps $x(t)$ to $x(t + \Delta t)$ where Δt is the periodic time for some point in the cycle.

The first part in the Poincaré Map method is to identify the ST-T complex. The start of the ST-T complex is chosen as starting $50ms$ after R as done in [5]. The end is found by using the formula

$$QT = 12\sqrt{RR} \tag{1}$$

found in [5]. Q is chosen as the point with smallest value within $100ms$ before R.

The Poincaré Map is then estimated for each time step. The map is assumed to be on the form $P(x) = x + s$ where $s \in \mathbb{R}$. The estimation is then done simply by taking the difference between the point in the current cycle with the point in the next cycle.

The value of s for the Poincaré map for heartbeat i is then plotted in a scatterplot against the same value for heartbeat $i+1$ for several heartbeats, the number of heartbeats is refered to as the window size of the estimator. If the values are clustered along even and odd beats then TWA is detected. The clustering detection is done by looking at the distance between the centroids of even and odd beats and that distance is the index. If the index is above a threshold then TWA is detected [5].

D. Performamce analysis

The data was analazyed visually to determine when the TWA truly occured. This was used to evaluate the performance of the methods. The performance was analyzed using five different metrics: *Accuracy*, *Sensitivity*, *Specificity*, *Positive Predictive Value* (PPV) and *Negative Predictive Value* (NPV).

The metrics are calculated as in equations 2 to 6 where N_{TP} is the number of true positives, N_{FP} is the number of false positives, N_{TN} is the number of true negatives and N_{FN} is the number of false negatives.

$$Accuracy = \frac{N_{TP} + N_{TN}}{N_{TP} + N_{TN} + N_{FP} + N_{FN}} \tag{2}$$

$$Sensitivity = \frac{N_{TP}}{N_{TP} + N_{FN}} \tag{3}$$

$$Specificity = \frac{N_{TN}}{N_{TN} + N_{FP}} \tag{4}$$

$$PPV = \frac{N_{TP}}{N_{TP} + N_{FP}} \tag{5}$$

$$NPV = \frac{N_{TN}}{N_{TN} + N_{FN}} \tag{6}$$

IV. Results

A. Human Data

Plot 1 shows the index created by the algorithm and the cutoff for when TWA is detected. The window size is set to 10, the baseline wander cancellation method was cubic splines and the cutoff was set to 0.3. As can be seen in the plot that alterans is detected between beat 30 and 35 and between beat 375 and 660.

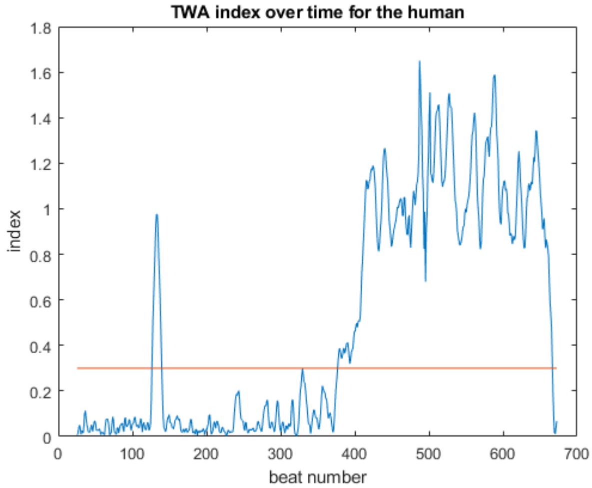

Fig. 1. The TWA index as calculated for the human data

In table I the performance of the default configuration of window size 10 cubic spline interpolation and cutoff 0.3 is compared to other configurations.

	default	window size 50	moving median baseline cancellation	cutoff 0.7
accuracy	0.9738	0.9556	0.9722	0.9167
sensitivity	0.9585	0.9078	0.9553	0.8275
specificity	0.9881	1	0.9881	1
PPV	0.9868	1	0.9868	1
NPV	0.9622	0.9211	0.9594	0.8612

TABLE I
PERFORMANCE METRICS FOR THE HUMAN DATA

B. Pig One

Plots 2 to 12 TWA index for the leads of pig 1 where alterans was detected. Here the threshold is 0.3, the window size is 50 and the interpolation method is cubic splines.

In table II the mean performance of the default configuration of window size 50 cubic spline interpolation and cutoff 0.3 is compared to other configurations.

	default	window size 10	moving median baseline cancellation	cutoff 0.7
accuracy	0.5881	0.6357	0.5648	0.3546
sensitivity	0.4532	0.5859	0.4373	0.1189
specificity	0.9577	0.7520	0.9141	1
PPV	0.9638	0.8568	0.9423	1
NPV	0.4251	0.4478	0.4007	0.2981

TABLE II
PERFORMANCE METRICS FOR THE FIRST PIG DATA

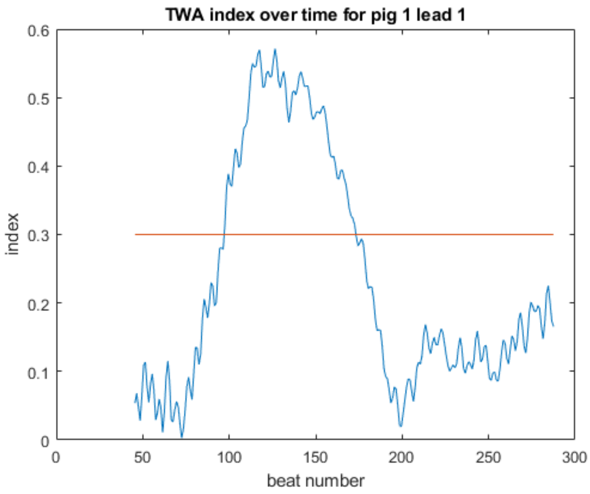

Fig. 2. The TWA index as calculated for lead one of the first pig

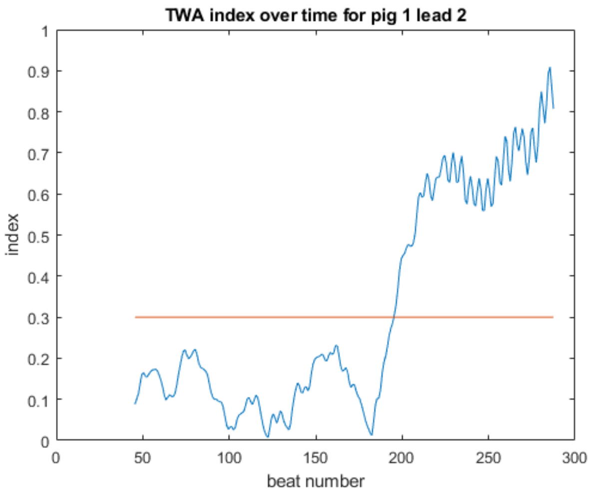

Fig. 3. The TWA index as calculated for lead two of the first pig

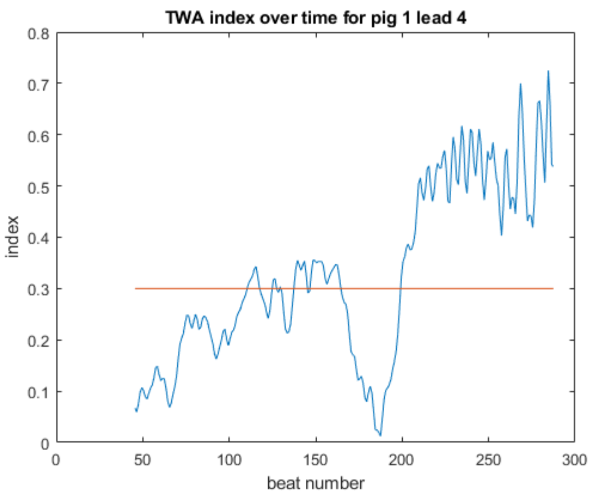

Fig. 4. The TWA index as calculated for lead four of the first pig

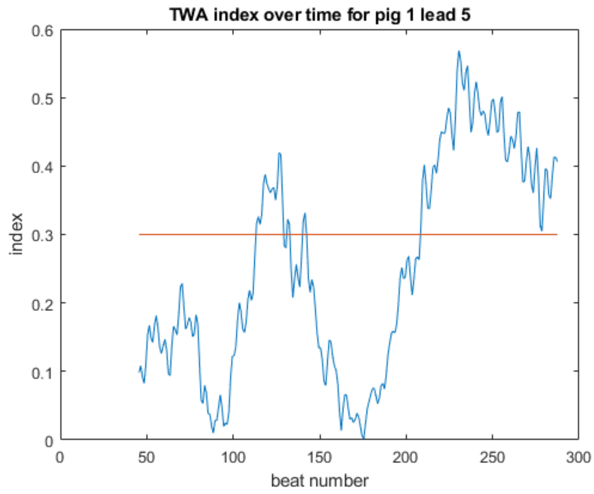

Fig. 5. The TWA index as calculated for lead five of the first pig

Fig. 6. The TWA index as calculated for lead six of the first pig

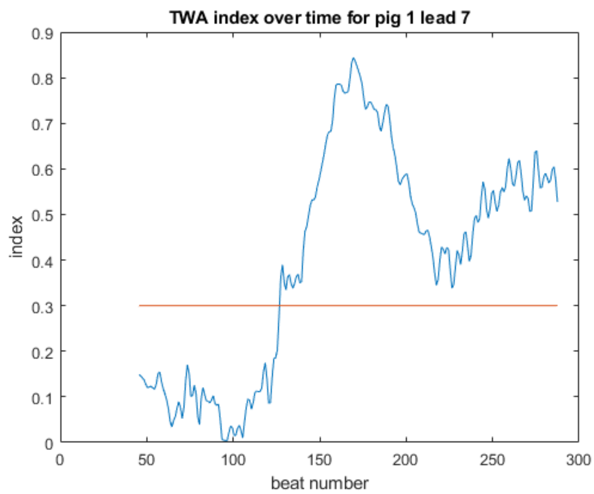

Fig. 7. The TWA index as calculated for lead seven of the first pig

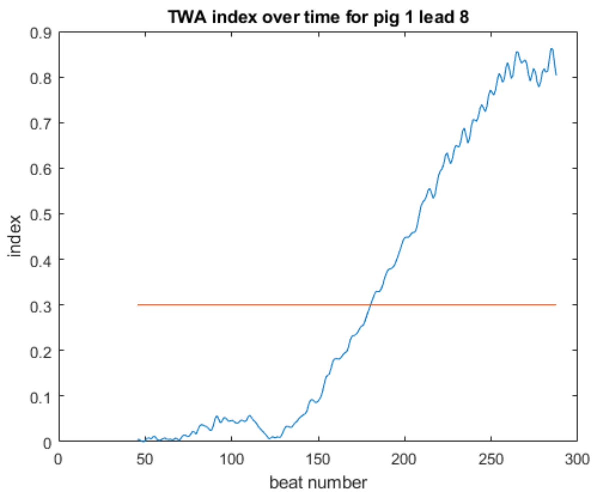

Fig. 8. The TWA index as calculated for lead eight of the first pig

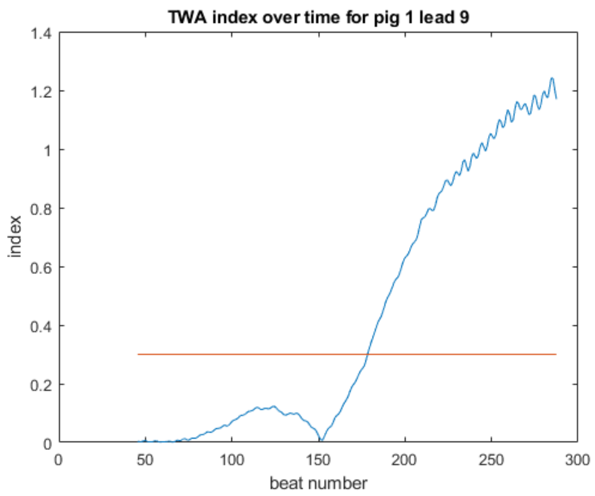

Fig. 9. The TWA index as calculated for lead nine of the first pig

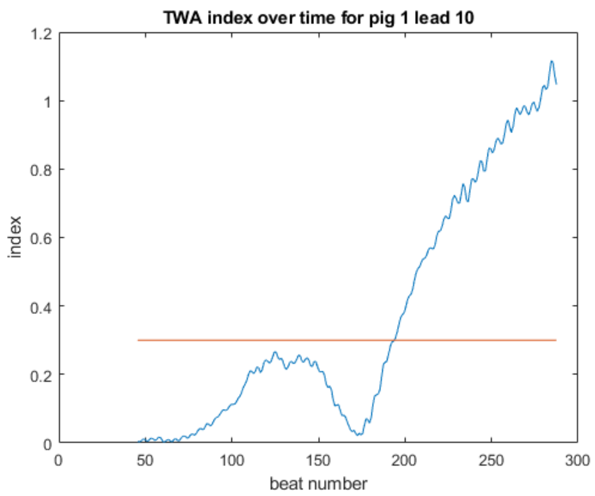

Fig. 10. The TWA index as calculated for the lead ten of the first pig

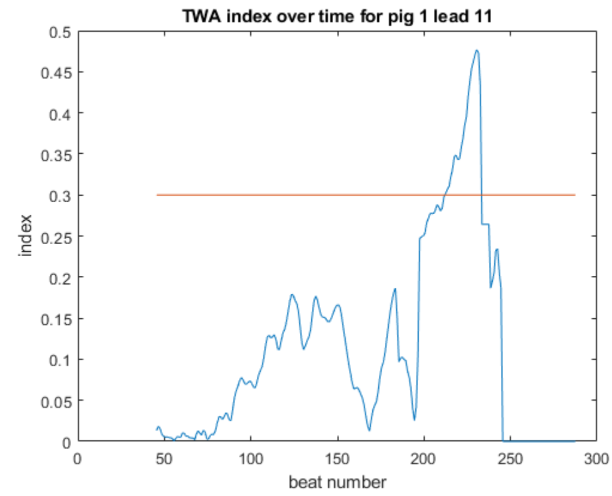

Fig. 11. The TWA index as calculated for lead eleven of the first pig

Fig. 12. The TWA index as calculated for lead twelve of the first pig

C. *Pig Two*

The plots showing TWA index and cutoff for the second pig with window size 10, cutoff 0.7 and moving median baseline wander cancellation is shown in figure 13 to 18

In table III the mean performance of the default configuration of window size 10 cubic spline interpolation and cutoff 0.7 is compared to other configurations.

	default	window size 50	cubic spline baseline cancellation	cutoff 0.3
accuracy	0.5776	0.4686	0.5462	0.5145
sensitivity	0.3630	0.1306	0.4078	0.5051
specificity	0.7743	0.8182	0.6730	0.5231
PPV	0.5208	0.3288	0.4375	0.4977
NPV	0.6042	0.4741	0.5912	0.6130

TABLE III
PERFORMANCE METRICS FOR THE SECOND PIG DATA

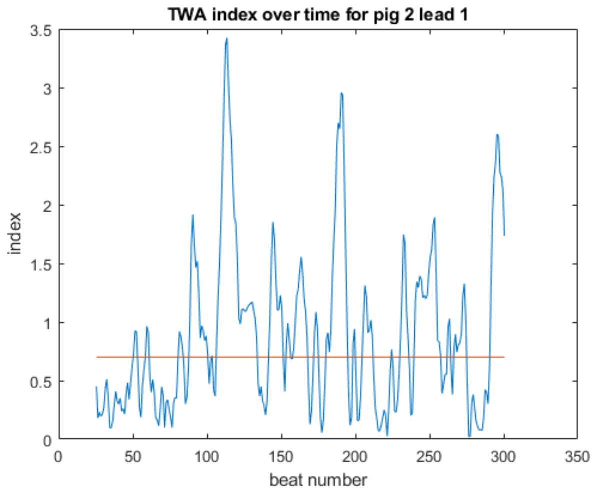

Fig. 13. The TWA index as calculated for lead one of the second pig

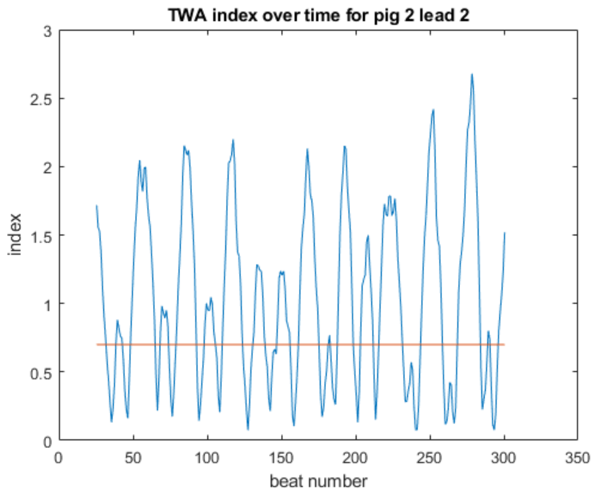

Fig. 14. The TWA index as calculated for lead two of the second pig

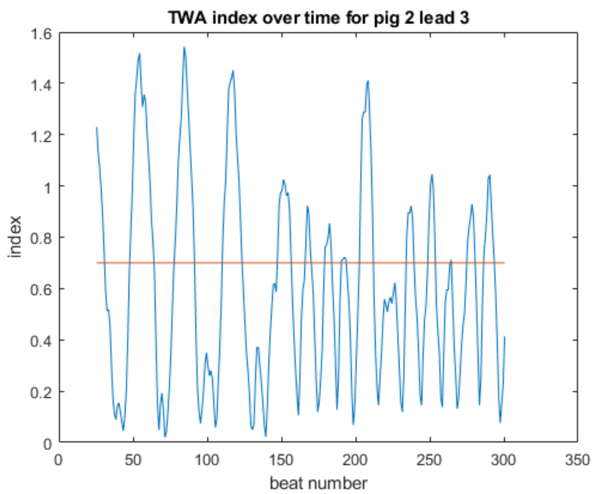

Fig. 15. The TWA index as calculated for lead three of the second pig

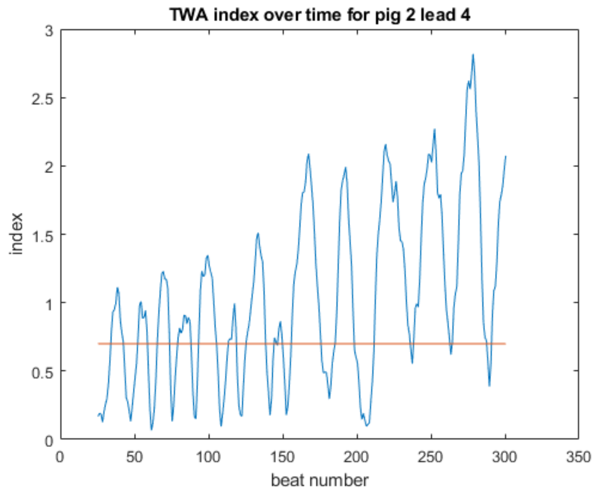

Fig. 16. The TWA index as calculated for lead four of the second pig

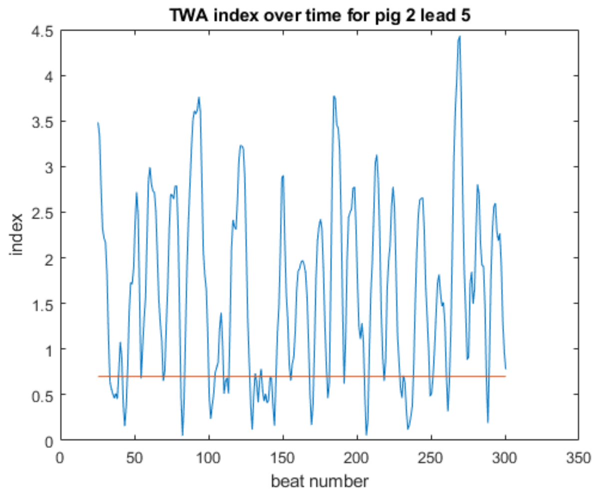

Fig. 17. The TWA index as calculated for lead five of the second pig

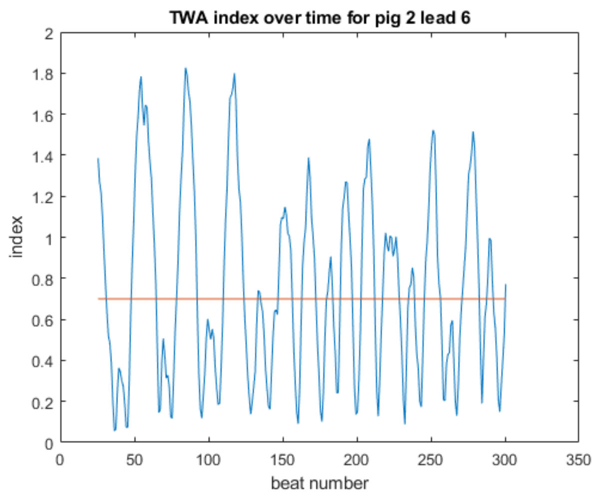

Fig. 18. The TWA index as calculated for lead six of the second pig

V. Discussion

The performance for the human data is on par with the performance of the Poincaré map method as implemented in [5] but the performance for the pig data is much worse. Some worsening of results is to be expected when dealing with noisier data and a more refined reprocessing stage could have probably mitigated some of it but it is still worse than expected.

As was hoped the Poincaré map method is capable of providing a prediction with a relatively small amount of samples and can therefore be used for dynamic tracking.

There seems to be a big difference in result when changing the cutoff. However, there does not seem to be a value that is best for all signals. I have two suggestions for what could be causing this. The first is that the normalization method is insufficient, the normalization method used is quite naive so this is likely. The second is that using the distance between centroids as an index is insufficient.

Something that can be said about the cutoff is that increasing the cutoff increases the PPV and the specificity and decreasing it increases the NPV and the sensitivity so if it is important that all positives really are positives then a higher cutoff would be adviseable and vice versa.

The difference when changing baseline removal method is small, even in the case of pig 2 where the PQ-segment isn't flat. The cubic spline method is much faster however so I would probably reccomend it if the PQ-segment isn't abnormal. A worthwhile extension of the report might be trying the performance of not removing the baseline wander.

Increasing or decreasing the the window size seems to have the same effect as increasing or decreasing the cutoff. Further experimentation with changing the two of them simultaneously is probably needed to draw any conclusions.

A suggestion for improvement is trying different methods for telling if the scatter plot contains two different clusters. This could for example be solved with machine learning or by normalizing the distance by how spread the points are. As stated earlier this could not only help with the accuracy but also to create a more general method.

Another improvement could be creating a predictor using more than one lead at a time, for example with a voting method.

VI. Conclusions

This implementation of the Poincaré map method seems to perform on par with the implementation described in [5] for data without much noise and with large T-waves. It performs worse at noisy data.

The choice of baseline removal method does not seem to matter much unless the baseline removal method is exceptionally unsuited for the signal. However other parameters need to be tweaked on a signal by signal basis when using this implementation of the Poincaré map method.

References

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