Automated Pacing Artifact Removal in Electrocardiograms

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Abstract — Electrocardiogram (ECG) is a basic and ubiquitous clinical tool to evaluate the electrical activity of the heart. Research and commercial software make automated calculations and interpretations from ECGs that have clinical value. An artificial pacemaker can however change the ECG and invalidate routine interpretation. Automated evaluation of paced ECGs is further hampered by electrical pacing artifacts that distort the physiological electrical signal. Sophisticated pacing systems like cardiac resynchronization therapy further complicate the problem by introducing pacing artifacts that are not only preceding but are also within the relevant ECG signal where they simply cannot be ignored. The pacing spike generates outliers that skews results and hinders both regression analysis and principal component analysis of the physiological signal. This is the first paper to show effective elimination of pacing spike outliers in ECGs. In order to eliminate pacing spikes, this paper proposes a novel filter and compares to prior techniques used in alternate fields. This filter uses modified Z-scores calculated from detrended data to locate outliers and replaces the spikes with a hyperbolic cosine function that connects the gap created from removing the spikes. The filtering improves the QRS area measurement by over 46% compared to median filtering and 65.2 % compared to unfiltered ECGs. The filter is fast (7.53 ms) and inexpensive.

I. Introduction

The electrical activity from normal or abnormal cardiac muscle during cardiac excitation is captured from the body surface in a standard fashion called 12-lead electrocardiogram (ECG). ECGs have been used to study the hearts of healthy and diseased individuals for over a century. Cardiologists are adept in interpreting ECGs to diagnose cardiac structure and rhythm disorders. The main components of ECGs, for every cardiac cycle, include the P wave from activation/depolarization of the atria, the QRS complex from depolarization of the main pumping chambers or ventricles, and the T wave from repolarization of ventricles. Automated algorithms have been developed to quantify voltages and durations of the P wave, the QRS complex and the T wave on different ECG leads [1]. A normal ECG signal is shown in Figure 1a. A biventricular paced ECG signal is shown in Figure 1b.

The QRS complex captures the electrically dyssynchronous activation of the ventricles during

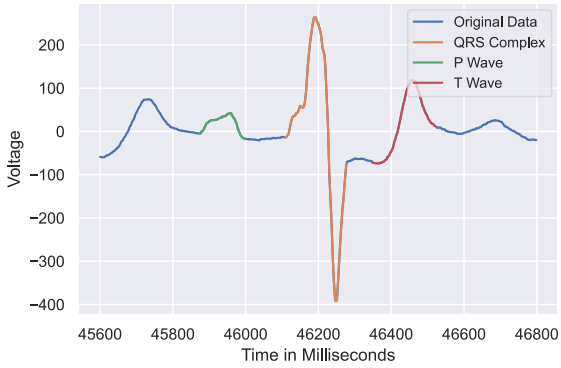

Figure 1a. ECG lead V6 without any pacing spikes.

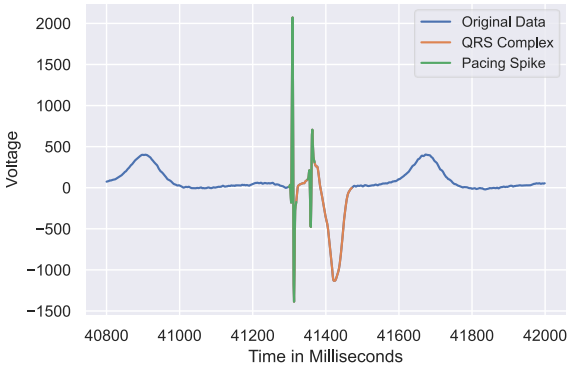

Figure 1b. ECG lead V6 with pacing spikes.

intrinsic cardiac electrical disease, e.g. left bundle branch block, or ventricular pacing from an artificial pacemaker. This results in a prolonged QRS duration and increased QRS voltages and is associated with ventricular failure [2]. Sophisticated pacemaker systems called cardiac resynchronization therapy (CRT) can try to resynchronize the ventricular activation with biventricular pacing and therefore narrow the QRS duration and reduce the QRS voltage. Artificial pacemakers, including CRT, introduce electrical artifacts when they deliver an electrical impulse to stimulate the heart. The pacing artifact or 'spike' skews the physiological ECG data [3]. This is even more relevant for CRT as some pacing spikes fall not at the onset but within the QRS complex itself. Such spikes can invalidate the automated calculation

of various ECG parameters e.g. QRS voltages and voltage-time integral (QRS area).

The QRS area or voltage-time-integral is a summary measure of the electrical activity across the ventricles [2][4] and has been validated as a superior measure of electrical dyssynchrony in patients with heart failure [2][3]. QRS area, after CRT is instituted, may have clinical and prognostic value. However, because of the artifacts generated by the pacing spikes, QRS area is challenging to algorithmically measure after a CRT pacemaker is inserted. This paper attempts to improve the measurement of the QRS area post-CRT by tackling the problem of pacing spikes.

There have been a number of different approaches to fixing pacing spike artifacts [5][6][7]. The most common approaches are low pass filters [8]. Low pass filters remove the signal above a certain frequency threshold, and high pass filters filter out everything below a certain threshold. Band pass filters remove frequencies above and below a certain 'band' or a set of high and low thresholds. Band pass filtering works on ECG because the physiological ECG signal has a characteristic frequency range. Noise of higher or lower frequency can be filtered out. Most ECG systems therefore band pass the ECG recording at 0.05-1 Hz for high pass and 100-150 Hz for low pass. Additionally, alternating current electrical power supply noise (50 Hz in most of world, 60 Hz in North and Central America) is filtered out using a notch filter that eliminates a very narrow frequency range surrounding the local power supply frequency. Unfortunately, these standard filters do not do a very good job of filtering out pacing spikes in the ECG.

To remove the pacing spikes, we needed a new approach to find and eliminate the spikes in the signal. The approach we created builds off of Whitaker and Hayes' work on despiking Raman spectra [9]. We present an approach to deal with spike outliers with the novel de-spiking median filter.

II. Data and Methods

The data for this paper was recorded on a Philips ECG machine with a standard 150 Hz lowpass filter and a 0.05 Hz highpass filter. The sampling rate is 1000 milliseconds, and the sample duration is 10 seconds. The system generates a normal averaged cardiac beat from the 10 second recording. The ECGs were recorded both before and after CRT. There is a large voltage artifact from the pacing spike in every CRT patient. We included 30 patients who are diverse in age, race, sex, and height/weight. The normal averaged beat was used for all our calculations. For each patient we included 8 independent ECG leads (leads I, II, V1, V2, V3, V4, V5, V6). The results were validated on diverse ECGs encompassing over 5000 separate ECG lead recordings.

Whitaker and Hayes' work on despiking Raman spectra [9] involved creating an algorithm to detect outliers using a modified Z-score of once differenced, detrended data and then applying a simple moving average to remove outliers. The Z-score in statistics describes how far from the mean a data point is by the number of standard deviations it is from the population mean. The standard Z-score is calculated as follows:

$$Z = (x - \mu) / \sigma \qquad (1)$$

Where μ is the population mean, σ is the standard deviation, and x is a single data point in the population. When using Z-scores for outlier detection, a standard threshold is 3.5 according to the American Society of Quality Control [10]. This can become an issue though as certain data signals have long baseline periods of zero signal which distorts the Z-score, such as ECGs. Whitaker and Hayes fixed this issue by using a modified Z-score approach which uses the Median Absolution Deviation. The modified Z-score is defined by

$$Z = 0.6745\,(x - M) \,/\, MAD \qquad (2)$$

Where MAD is equal to the median of the absolute deviations from the population median or

$$MAD = median(|x - \tilde{x}|) \qquad (3)$$

The use of a modified Z-score is recommended by the National Institute of Standards and Technology, NIST, as an outlier detection method [11].

With ECG data, there are long periods of time between the T wave, the P wave, and the QRS complex. These electrical baseline periods skew the population mean and make the QRS complex signal fall out of that 3.5 Z-score threshold. Every heart is different and can have various structural or electrical diseases or scar tissue that can drastically change the amplitude and relative frequencies of the QRS complex. This makes ECG data unpredictable and hard to have a set threshold for every patient. Some patients may need a threshold of 8 and others a threshold of 300 to not delete any of the physiological QRS complex signal from the data.

To address this, we needed to create an automatically adjusting threshold. The new threshold approach involves calculating the modified Z-score of the once differenced, detrended data. Next, we found the peak within the QRS complex modified Z-score that was lower than a criterion. The criterion is the value of the 98th percentile of the modified Z-score plus 40. We then set the threshold to plus 1 above the peak that was

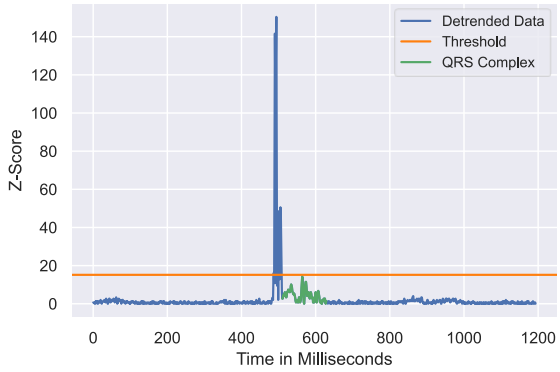

Figure 2. Automatic threshold detection of lead V4 with QRS complex highlighted.

less than the criterion within the QRS complex (Figure 2). This ensures that the threshold we choose is less than any outlier in the data. The selection choice of 98th percentile as the cutoff was due to the nature of the outliers. They are typically the tallest datapoints in the dataset and are always above the 98% percentile. If a patient is ventricularly paced, the pacing outlier could fall within the QRS complex. Since the outlier will have a higher Z-score than the peak of the QRS complex, we could not just set the threshold to the highest peak within the QRS complex. Instead, we used the 98th percentile to find the non-outlier peak of the QRS complex. This proved to be more stable and robust than just taking the max value in the QRS complex as that could set an outlier as the threshold of the filter, defeating the purpose of the filter.

The additional 40 in the cutoff criteria is based on patients who are not paced and have no outliers. With no outliers, the QRS complex itself would be the 100th percentile, or max datapoint, in the signal. So, the filter would automatically delete the tip of the QRS complex signal. To make the filter robust against this, we added a flat value to it. The usual range of non-paced patients' max Z-score is 10-20. The initial flat value we used was 20 to ensure that we did not include any outliers and also did not delete any physiological signal. This did not work for some of our tachycardic patients whose QRS complexes are unnaturally narrow. Patients with this condition had max Z-scores that ranged from 50-70. We settled with 40 as the flat value as it was the most statistically stable value across a verity of patient conditions.

Whitaker and Hayes' removed the spike by the neighbor interpolation method. Which is interpolating the mean of the values of the immediate data points before and after the spike that are below the threshold. This eliminates the spike outlier and smooths out the signal while introducing a negligible amount of noise to Raman spectra data. When this approach was done for ECG data, it did not work nearly as well because QRS complexes have much higher thresholds compared to Raman spectra. This left behind quite a bit of noise below the threshold. A median filter was applied after despiking to help with this problem. It achieved favorable results but was still not perfect. The novel approach from this paper instead simply deletes the data points above the threshold and fills in the gap that is left behind with a hyperbolic cosine function; much like the cubic spline interpolation method with a small difference in how the cosine function fills in the gap. This was more stable as many of the data points left behind from Whitaker and Hayes' method were still tall, as we see in Figure 3 around 300 ms.

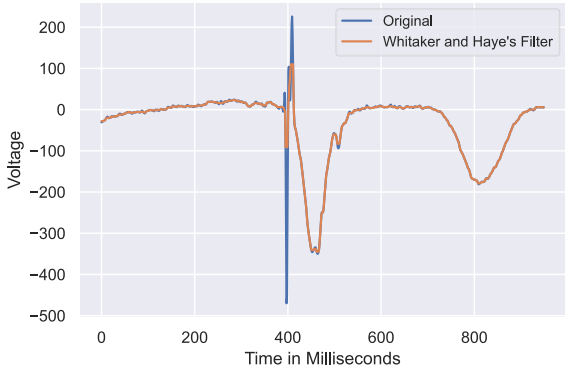

Figure 3. Whitaker and Hayes' algorithm on lead V4.

So, when the moving average interpolation happened, the noise that remained created a much smaller spike but still enough to invalidate calculations and analysis on the data. Deleting the data completely removed any trace of the spike, and it is relatively easy to interpolate the presumed physiological signal from distant points.

The choice of the hyperbolic cosine spline, over a more traditional sinus or polynomial spline, was due to the nature of the data. ECG data typically ramps up voltage slowly, so polynomial curves are too

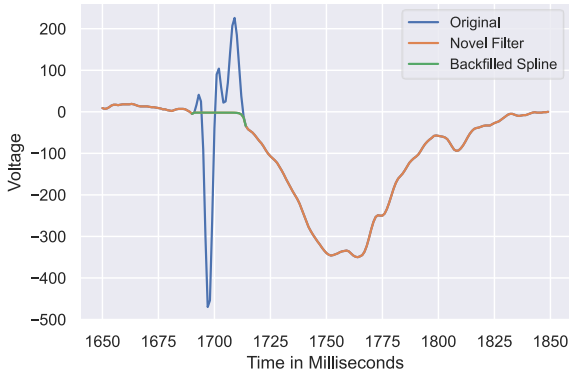

Figure 4. Demonstration of novel filter on lead V4.

aggressive to be natural on ECGs. The hyperbolic cosine curves are more gradual and follow the trend of the data much more closely compared to sinus and polynomial curves.

Figure 4 shows an example of how the novel filter works. It deletes all of the original information between the orange lines and backfills them with a hyperbolic cosine spline.

After interpolation, a median filter is applied to the data to eliminate any residual noise in the signal. This essentially acts as an intelligent band pass filter that filters out the high frequency outliers with dynamic precision and robustly cleans up low frequency noise. In order to make the filter more robust, we added a clause in the algorithm to revert the filtering process if the change in area between the original and new signal data was greater than 15%. Since the outliers are very narrow, when they are deleted it should not change the overall area much. If the area has a large change, we know that some of the QRS complex was altered and the change needs to be reverted. The use of 15% as the cut off was decided by the average and standard deviation of change in area in all our patients.

This method allows us to dynamically filter all outliers with extreme precision. This also allows for near instantaneous filtering and fixing of ECG data at 7.53 milliseconds per lead averaged over 4,632 leads (time was taken on a desktop PC with a Ryzen 7 1700X CPU and 16 GB of 2400 Hz DDR4 RAM).

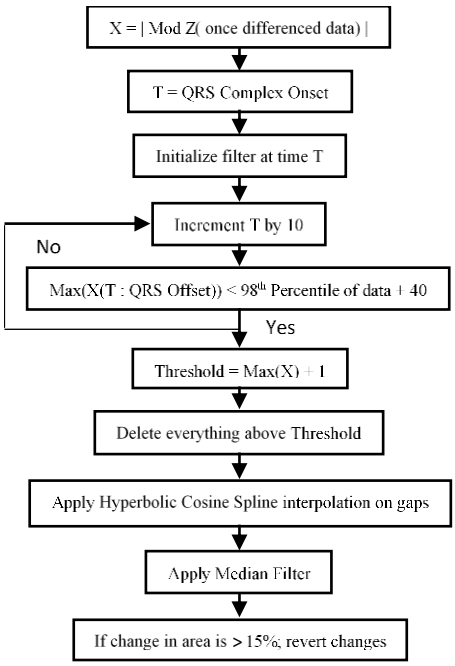

Figure 5. Basic diagram of algorithm.

III. Results

The novel filter successfully filtered out all spikes on all patients with pacing spikes from CRT. It did not have any effect on data without spikes which shows that the filter will only target outliers. The novel filter performed better than Whitaker and Hayes' despiking algorithm even with a median filter applied afterward as demonstrated in Figure 6.

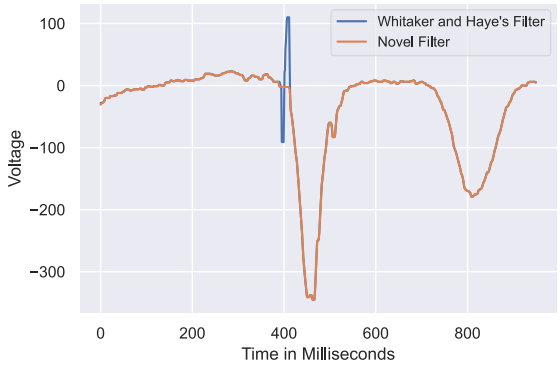

Figure 6. Comparing novel filter with Whitaker and Hayes' algorithm on lead V4.

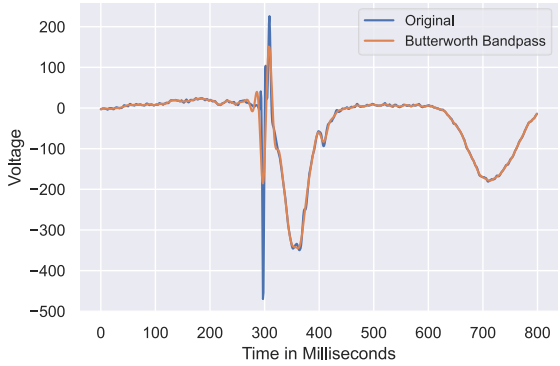

Figure 7. Bandpass filter compared to the original data on lead V4.

It also preforms better than a 60 Hz digital Butterworth bandpass filter with a forward and backward pass. The bandpass filter does remove most of the spike, but it also distorts the QRS complex as seen in Figure 7. There is also considerable noise added before the spike.

The novel filter does not distort the physiological signal at all. It also works well on every lead. Here are some examples of the novel filter versus Whitaker and Hayes' filter (figures 8, 9, and 10). This filter was

tested on a sample size of around 5000 leads from a wide variety of patients with various heart conditions.

The filter consistently far outperformed Whitaker and Hayes' algorithm and any bandpass filter as shown in Tables 1 and 2, showing data from 8 leads each in 5 separate CRT patients. Table 1 shows the average reduction in area of the outliers in nanovolt-seconds for each filter compared to the original (higher is better).

Table 1. Comparing average removed area of each filter on each lead.

Leads	Whitaker and Hayes'	Novel Filter
Lead I	18.9%	70.9%
Lead II	19.1%	60.1%
Lead V1	19.7%	69.6%
Lead V2	18.4%	65.3%
Lead V3	16.5%	67.6%
Lead V4	22.2%	78.8%
Lead V5	20.2%	70%
Lead V6	17.8%	38.9%

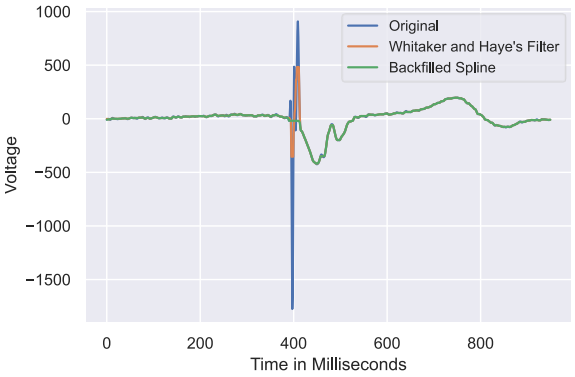

Figure 8. Comparing novel filter with Whitaker and Hayes' algorithm on lead II.

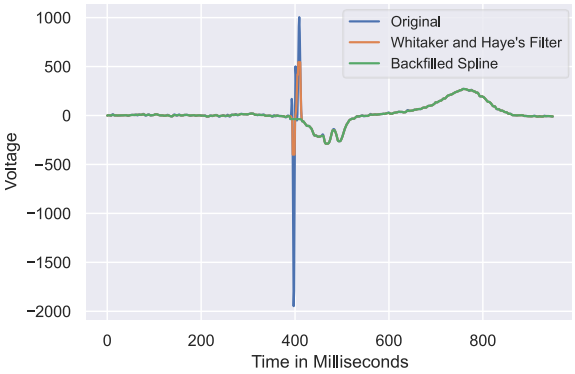

Figure 9. Comparing novel filter with Whitaker and Hayes' algorithm on lead I.

Table 2 compares the total amplitude (microvolts) of the spike before and after each filtering technique (lower is better). With the largest change being a 3,274.5 microvolt reduction in spike amplitude. These results are the average of 40 leads from 5 CRT patients. Lead V6's drop in performance is a result of the size of that lead's outlier and not a problem with the novel filter. Also, the reason the results are not a 100% reduction in amplitude and area is due to the location of each outlier. Since the spikes are occurring inside the signal and not at the baseline the amplitude and area will not become 0 even if perfectly filtered.

Table 2. Comparing average total amplitude of spike on each lead.

Leads	Original Data	Whitaker and Hayes'	Novel Filter
Lead I	1030.86	370.64	47.86
Lead II	1045.53	394.51	69.53
Lead V1	1457.30	690.38	57.18
Lead V2	1531.2	745.49	71.11
Lead V3	1290.52	804.64	83.77
Lead V4	1239.25	689.10	63.39
Lead V5	1105.84	536.19	80.40
Lead V6	917.64	370.72	148.43

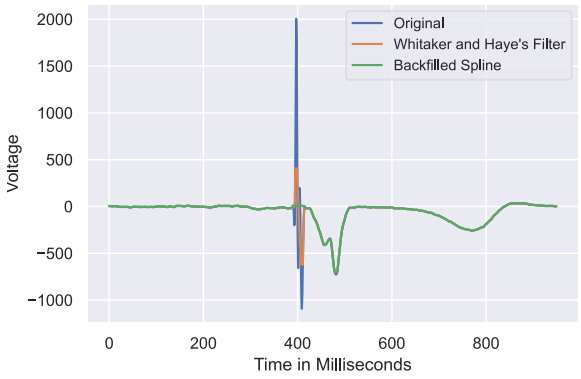

Figure 10. Comparing novel filter with Whitaker and Hayes' algorithm on lead V1.

IV. Summary

We present a new dynamic filter to process spike outliers that improves upon the Whitaker and Hayes' despiking algorithm [9] and apply it to ECG data. The outlier detection is done using the modified Z-score of detrended data. The filter interpolates the new signal

from the gap generated from deleting data above the dynamic threshold and applies a median filter to smooth out any noise.

The novel filtering improves the QRS area measurement on average by over 46% compared to Whitaker and Haye's filter and 65.2 % compared to unfiltered ECGs. The filtering has been demonstrated to be robust and reliable on 12 lead ECG data in many patients spanning a variety of cardiovascular conditions. This filter is computationally inexpensive, fast (7.53ms per lead), and can be applied on any platform. This filter can also be applied for any type of signal or time series data and can be applied generally across domains with only tuning of the percentile of Z-scores and the flat value of the filter for specific domains.

Acknowledgments

Research reported in this publication was supported by The University of Kansas. The content is solely the responsibility of the authors and does not necessarily represent the official views of The University of Kansas. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of The University of Kansas.

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