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# Automated Pacing Artifact Removal in Electrocardiograms

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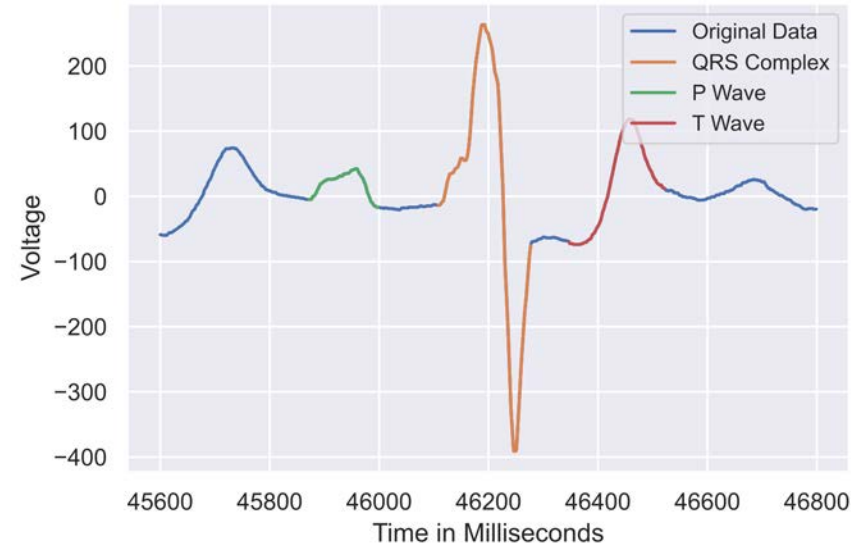
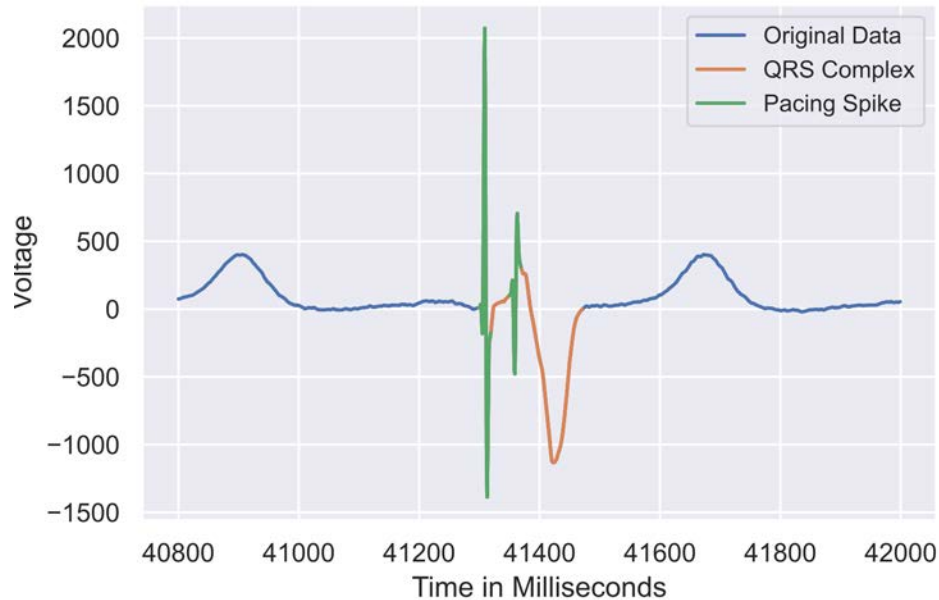
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## Abstract

- **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 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 per patient) and inexpensive.**

# 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).
- 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.



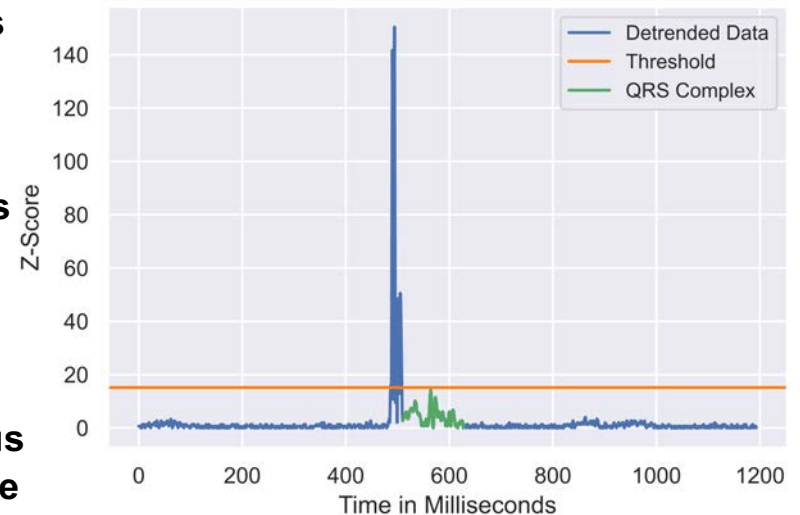
- Artificial pacemakers, including CRT, introduce electrical artifacts when they deliver an electrical impulse to stimulate the heart. The pacing artifact or 'spike' skews the physiological ECG data.
- This is even more relevant for CRT as some pacing spikes fall not at the onset but within the QRS complex itself. Such spikes can invalidate the automated calculation of various ECG parameters e.g. QRS voltages and voltage-time integral (QRS area).

## Data

- 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.

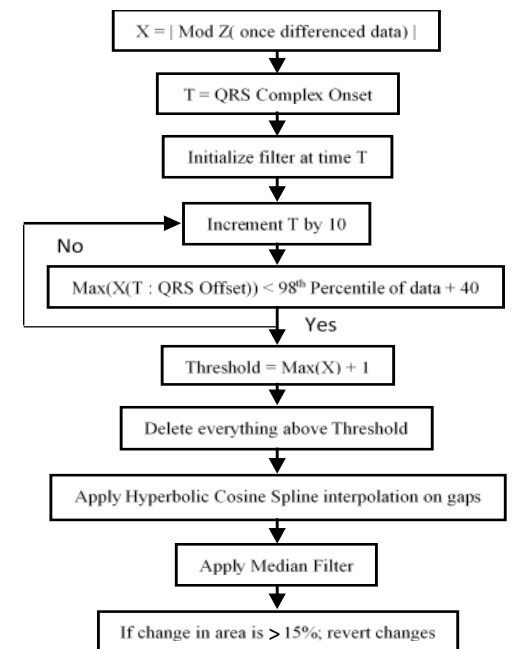
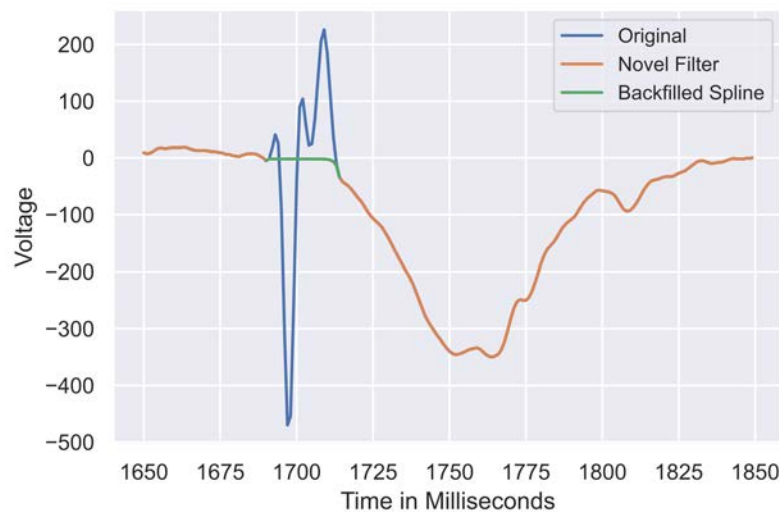
## Methods

- Whitaker and Hayes' work on despiking Raman spectra 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.
- 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 a standard 3.5 Z-score threshold for detecting outliers.
- Every heart is different and can have various conditions that can drastically change the amplitude and frequencies of the QRS complex. This makes ECG data unpredictable and hard to have a set threshold for every patient.
- 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 98<sup>th</sup> percentile of the modified Z-score plus 40. We then set the threshold to plus 1 above the peak that was less than the criterion within the QRS complex.



## Methods

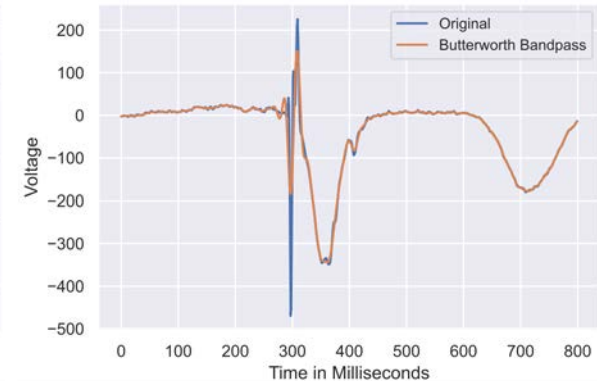
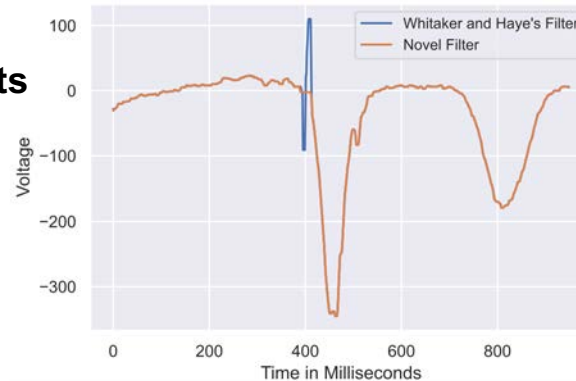
- Whitaker and Hayes' removed the spike by the neighbor interpolation method. This eliminates the spike outlier to Raman spectra data. When this approach was done for ECG data, it did not work nearly as well.
- The novel approach from this paper instead simply deletes the data points above the threshold and fills in the gap that is left behind with a hyperbolic cosine function; much like the cubic spline interpolation method.
- After interpolation, a median filter is applied to the data to eliminate any residual noise in the signal.
- If the change in voltage area between the original and new signal data was greater than 15%, the algorithm will revert the filtering process.



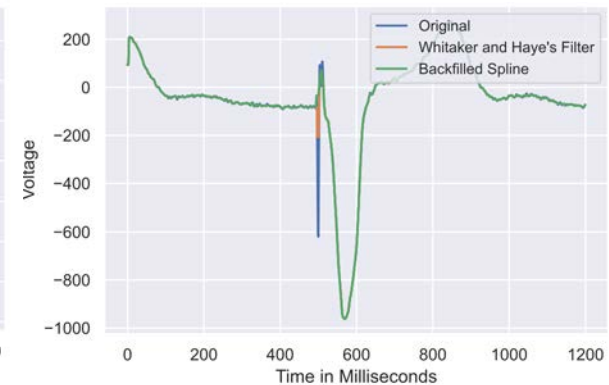
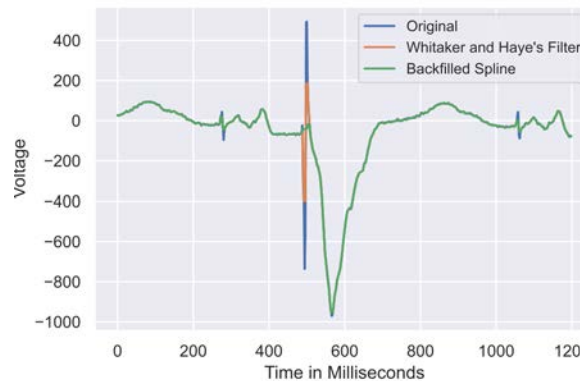
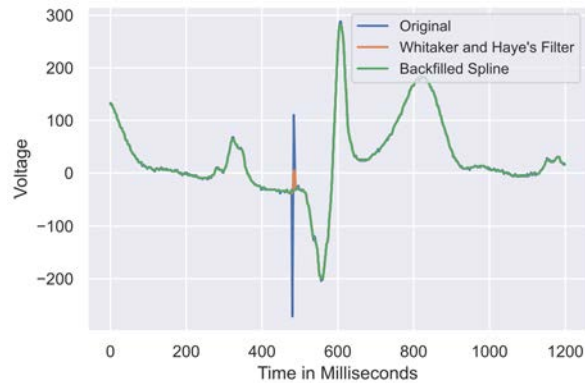
# Experimental Results

- The novel filter successfully filtered out all spikes on patients with pacing spikes from CRT. It did not have any effect on data without pacing spikes.
- It performs better than a 60 Hz digital Butterworth bandpass filter with a forward and backward pass.

## Novel Filter Vs Old Methods

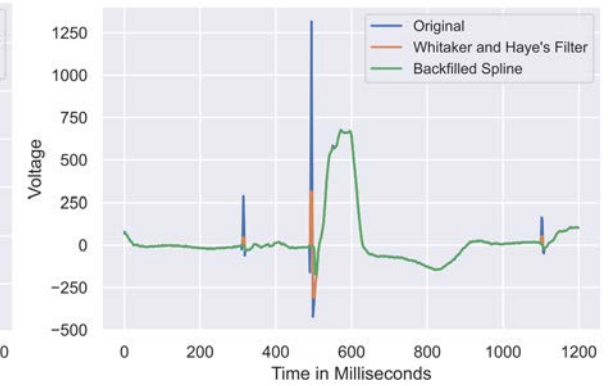
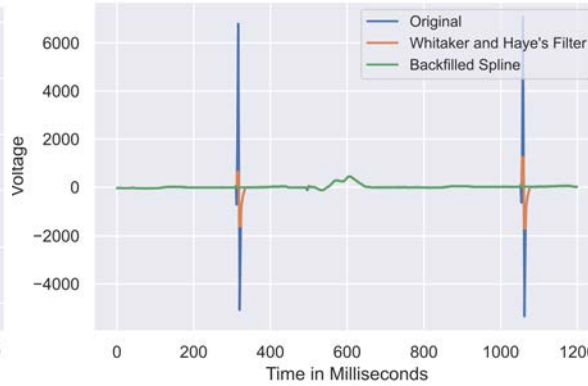
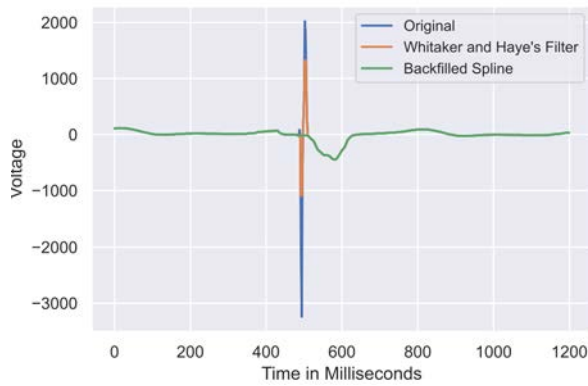


## Normal Voltage CRT Pacing Spike Outliers

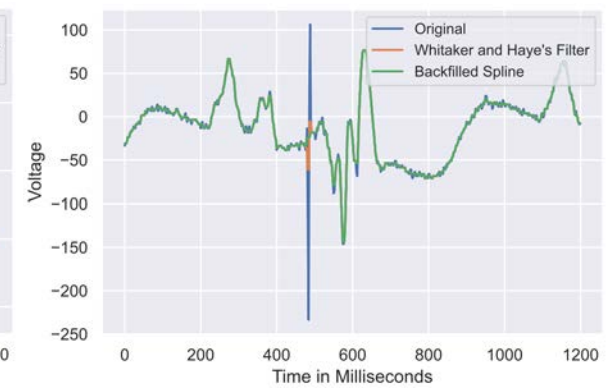
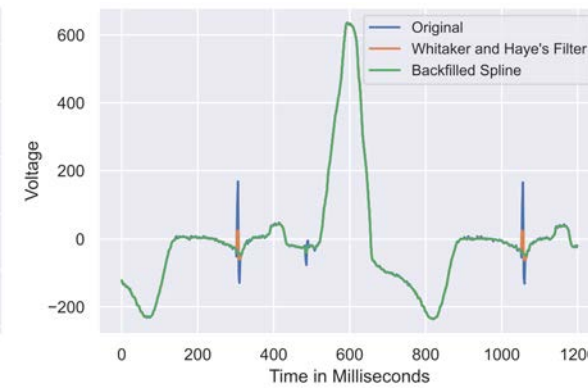
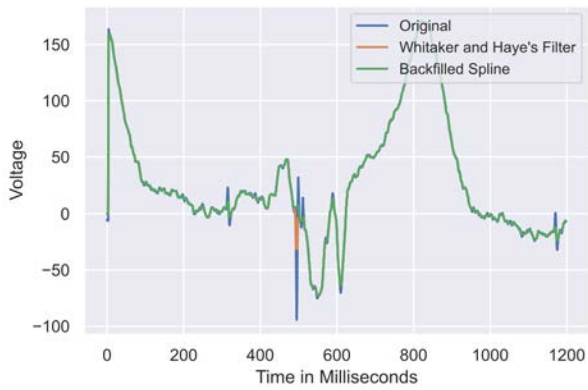


# Experimental Results

## High Voltage CRT Pacing Spike Outliers



## Low Voltage CRT Pacing Spike Outliers





## Experimental Results

- The filter consistently far outperformed Whitaker and Hayes' algorithm and any bandpass filter.
- Table 1 shows the average reduction in area of the outliers in nanovolt-seconds for each filter compared to the original (higher is better).

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%

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

- Table 2 compares the average total amplitude (microvolts) of the spike before and after each filtering technique (lower is better). With the largest change in the dataset being a 3,274.5 microvolt reduction in spike amplitude.

## Summary

- **We present a new dynamic filter to process spike outliers that improves upon the Whitaker and Hayes' despiking algorithm 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 Hays'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

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