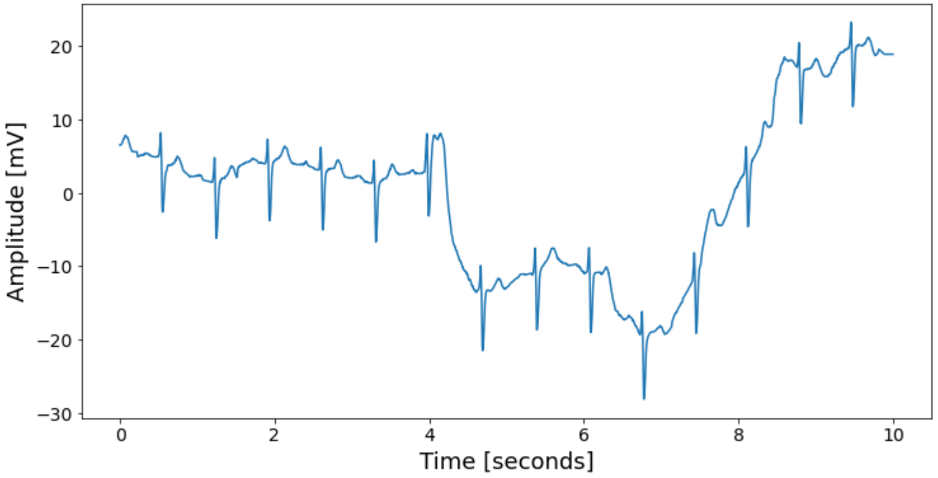
Understanding data

To better manipulate the data, it is important to understand what are true measurement mistakes in each signal. We verified that some particular effects were indeed due to non-dx related causes.

Some of these effects and causes were:

- Sudden spikes in the signal could be caused by the ECG machine not recording it correctly.
- Tendency, cyclic, or other non-constant behaviour could be due to muscular movements or electrodes misplacement.
- Prolonged stationary values could be generated by an overall error or disconnection.



We are working on some ways to correct the signals. However, we still need an expert eye to assess whether there is still more to do, as well as to further clarify some doubts regarding how much we can process a signal without losing information.

Proposed correction ideas

We worked on some ideas to correct and standardize the signals. These work in a top to bottom way, with each idea stacking on top of the previous one. To identify them, we will be calling them:

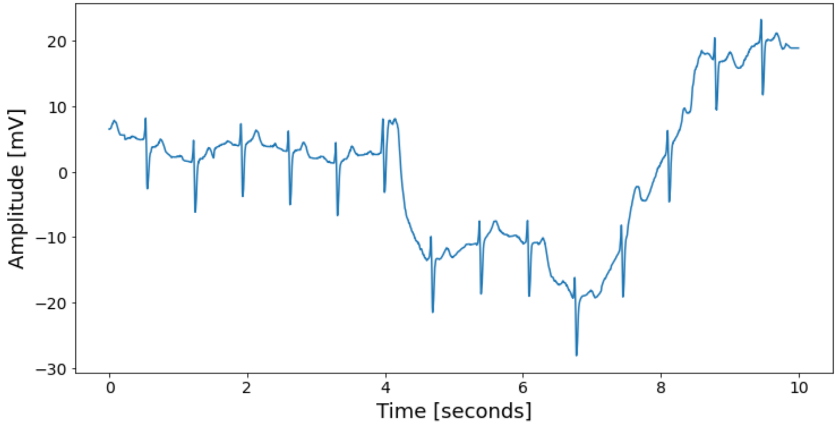
- **Smooth** : Have the signal be centered around 0.
- **Quantiles** : Have some upper and lower spikes cut from the signal.
- **Butter** : Apply a Butterworth smoothing filter to reduce noise.

Looking into the The PhysioNet/Computing in Cardiology Challenge 2020 top #1 team's code, they used a technique to shorten the wave's frequency range, which in a way performs the 3 steps presented above:

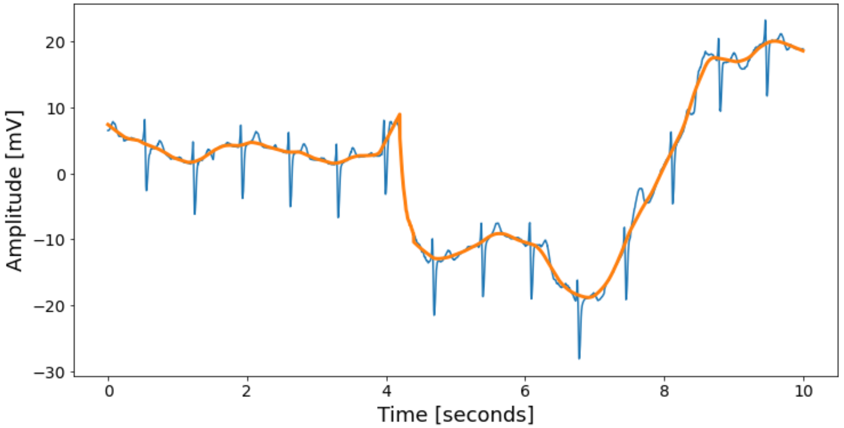
- **Bandpass** : Apply an FIR bandpass filter to correct the signals.

To understand what each of them tries to accomplish, we will apply them to a single example. Then, we will present some examples where each effect can be compared visually. It's worth mentioning now that there are cons, pros and limitations for each methodology.

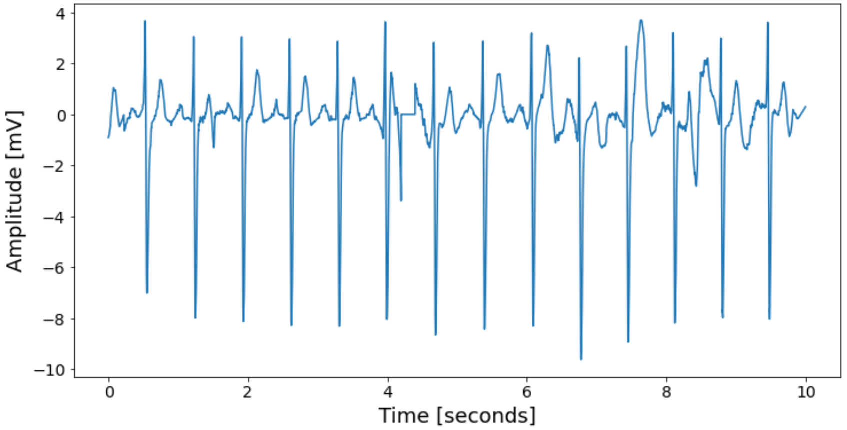
Smooth



Original Signal : Used for reference. Note how it is not centered around 0 but rather has a strange fall at around 4 seconds. Then, at around 7 seconds it starts going up linearly.

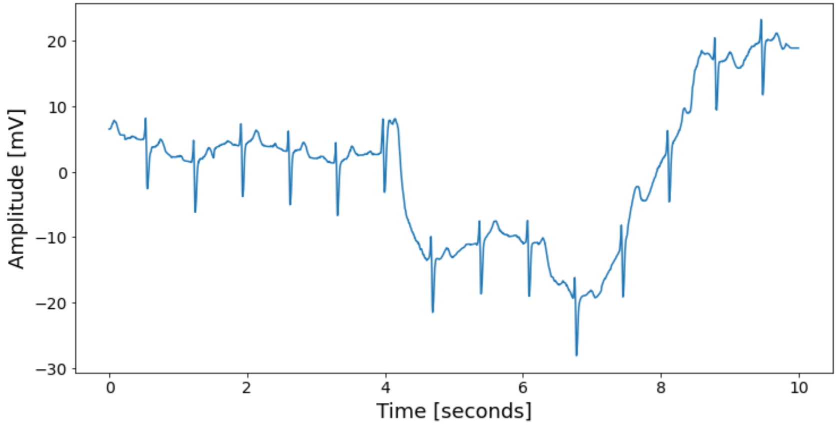


Fitted Tendency : We fit a line that follows whichever tendency the signal shows. Note how we are not fitting important segments such as the QRS complex or the P and T waves. This is because those segments do contain information about the diagnoses, while the tendency is just noise.

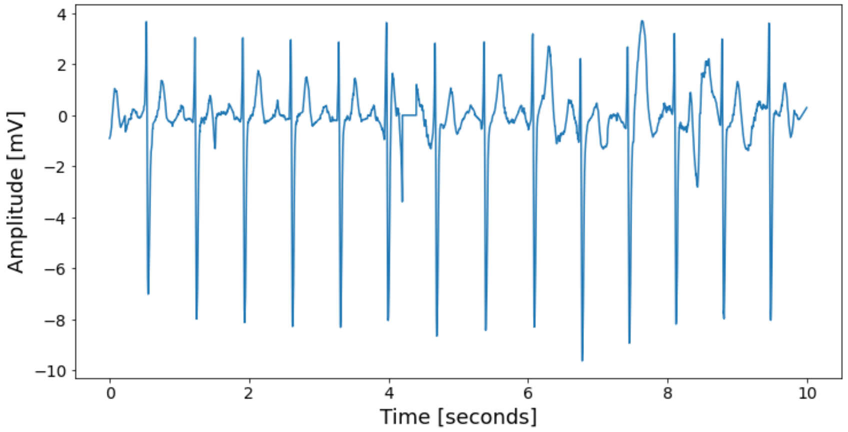


Smoothed Signal : We substract the Fitted Tendency from the Original Signal to get a 0 centered signal. This initial transformation seems to retain some of the most important aspects of the signal; however, there might still be noise within the heights of the QRS complexes.

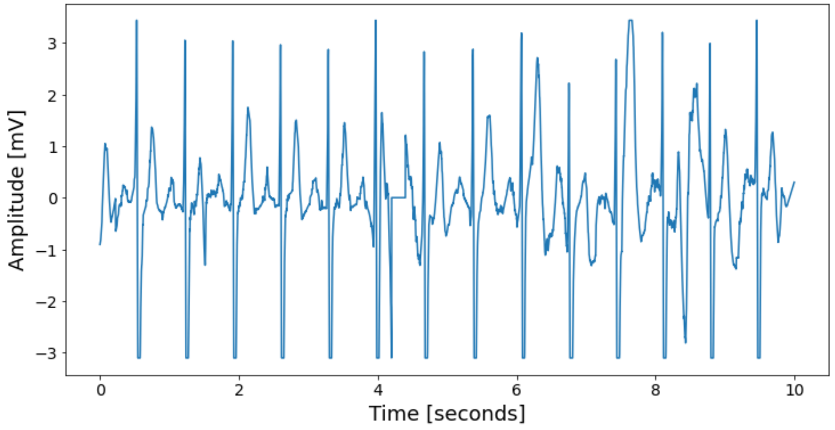
Quantiles



Original Signal : Used for reference.

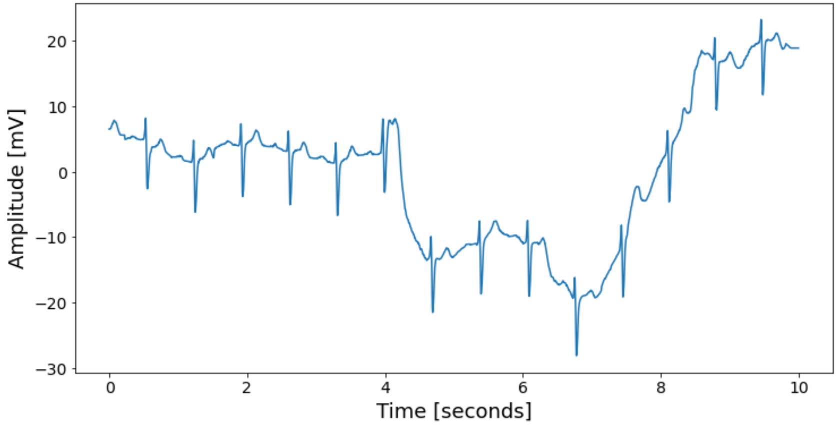


Smooth Signal : Used for reference. Note how the amplitude still occupies a very wide range, from -10 to 4. Such high and particularly low spikes could be due to noise (or maybe the diagnoses due match with such spikes, more examples to verify this will be presented later).

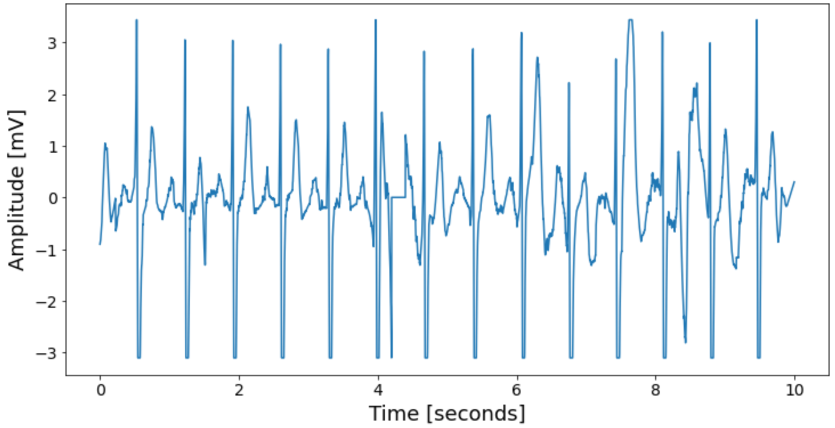


Quantiles Signal : We calculate some upper and lower quantiles of the signal, and make a cut for each value that is not whithin that range. So, any value below(above) the lower(upper) quantile is set to be the lower(upper) quantile. This overall reduces the amplitude, but there might be some loss of information.

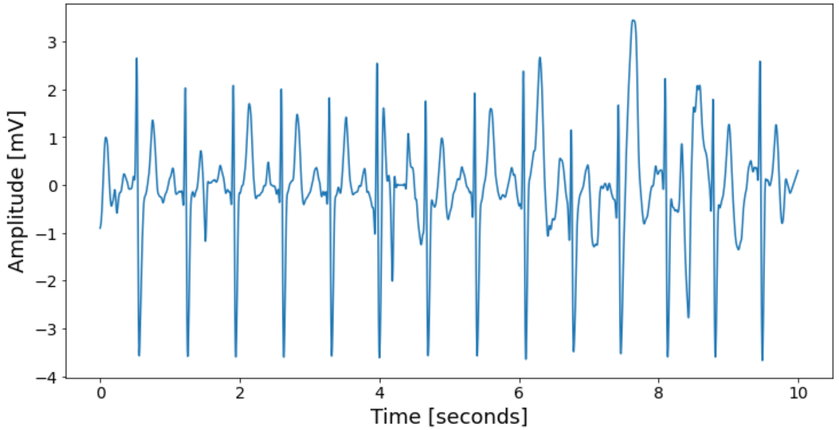
Butter



Original Signal : Used for reference.



Quantiles Signal : There still seems to be some noise within the signal. We could probably get by with it. Nonetheless, if removing said noise would help us improve the accuracy of our predictions, then it might be worth trying



Butter Signal : We apply a Butterworth filter to further reduce noise in the signal. Within the size of the image, it is a little hard to detect some of the changes, so we make a zoom in on the next slide.

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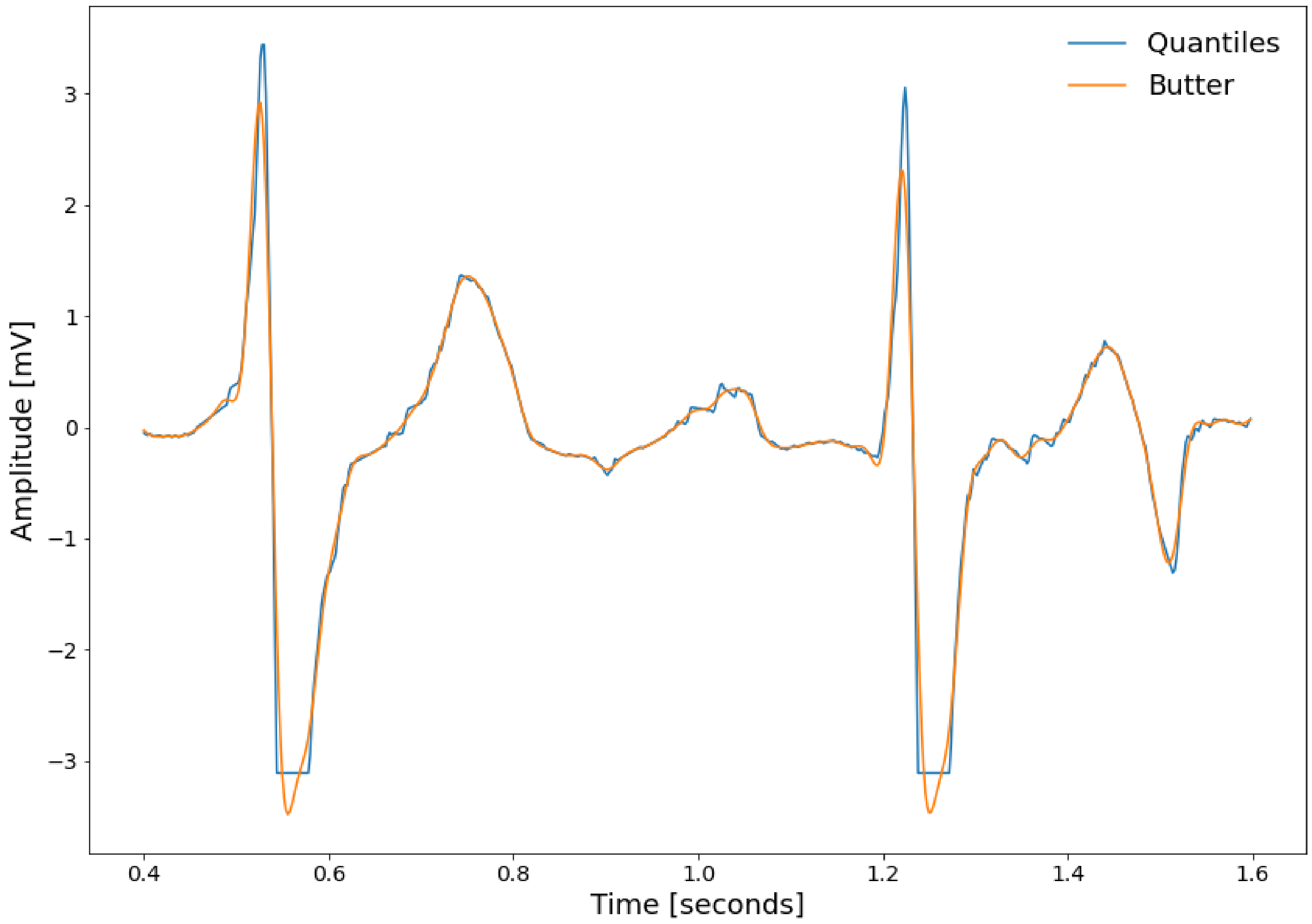
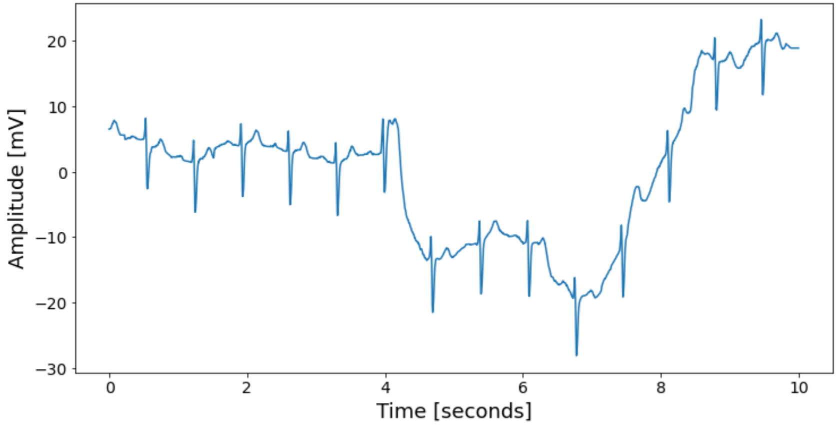
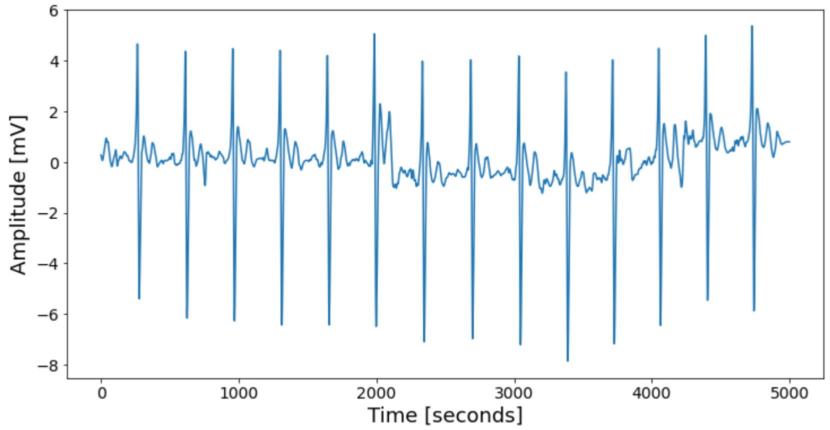


Butter Signal : We can see that the filter reduced little chunks of noise all around the signal. Also, it corrects a little bit the rough cuts made in the Quantiles step.

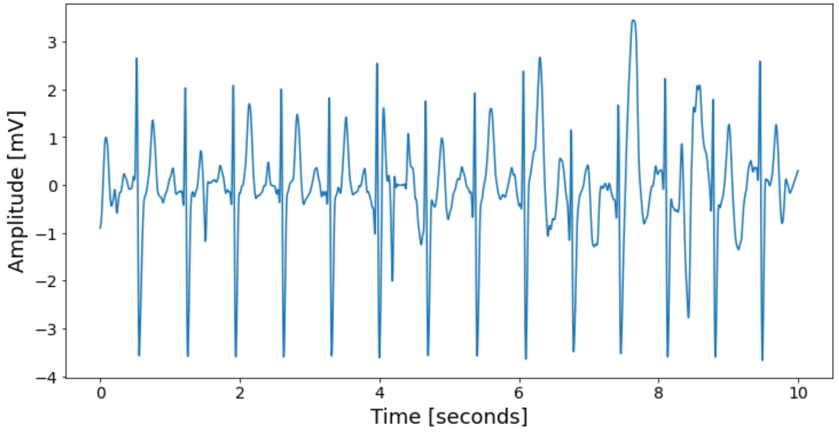
Bandpass



Original Signal : Used for reference.

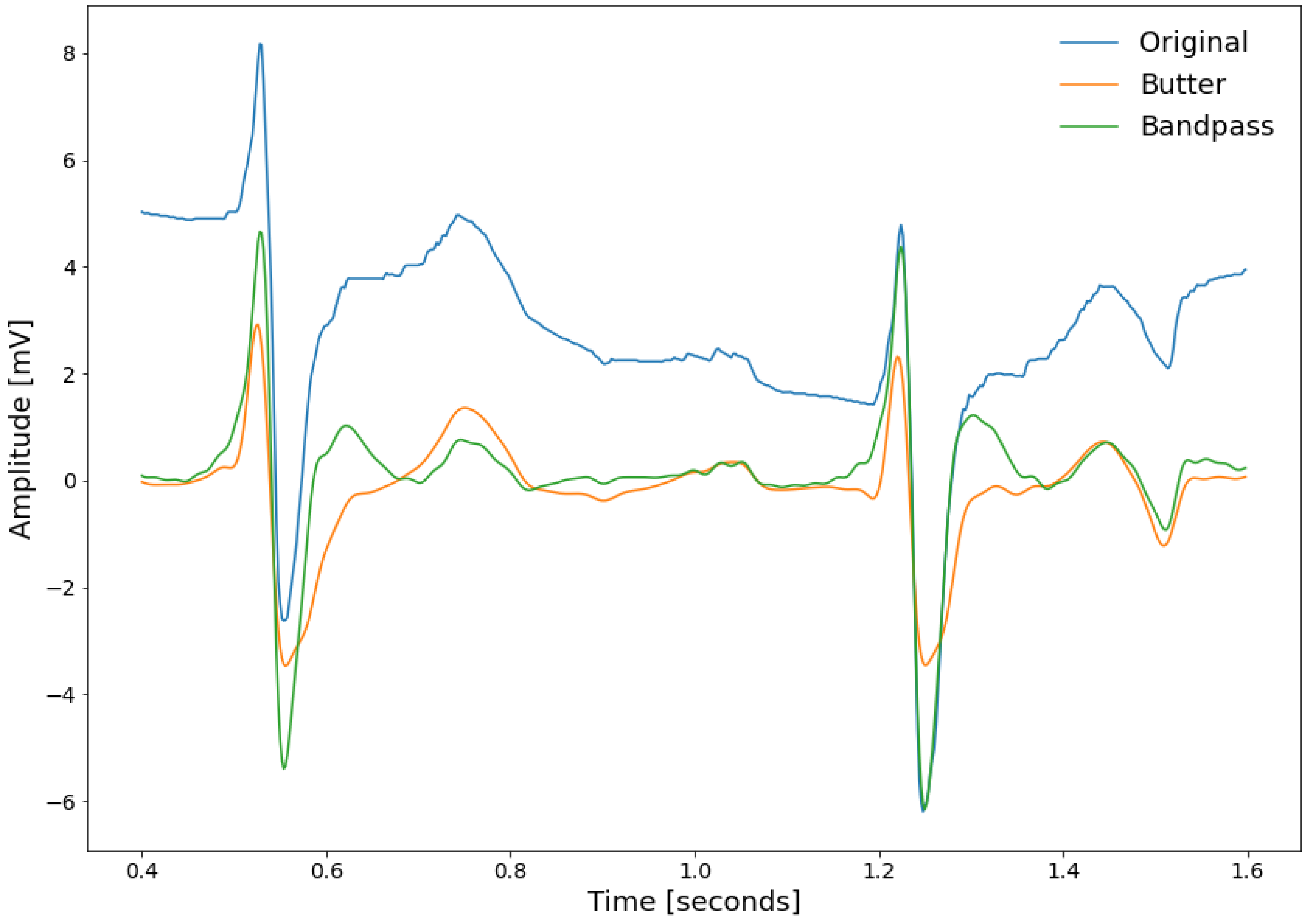


Bandpass Signal : We fit an FIR bandpass filter to the signal. This is the method used by the number #1 team in the Physionet Challenge. It looks quite similar to the 3 cascade transformations that we performed with our own methodology, except perhaphs for the Quantiles step.



Butter Signal : Used for reference. Note there are similarities with this filtered signal and the Bandpass one: Centered around 0, overall range reduction, kind of smooth everywhere. But as we will see in the next slide, there are some notable differences.

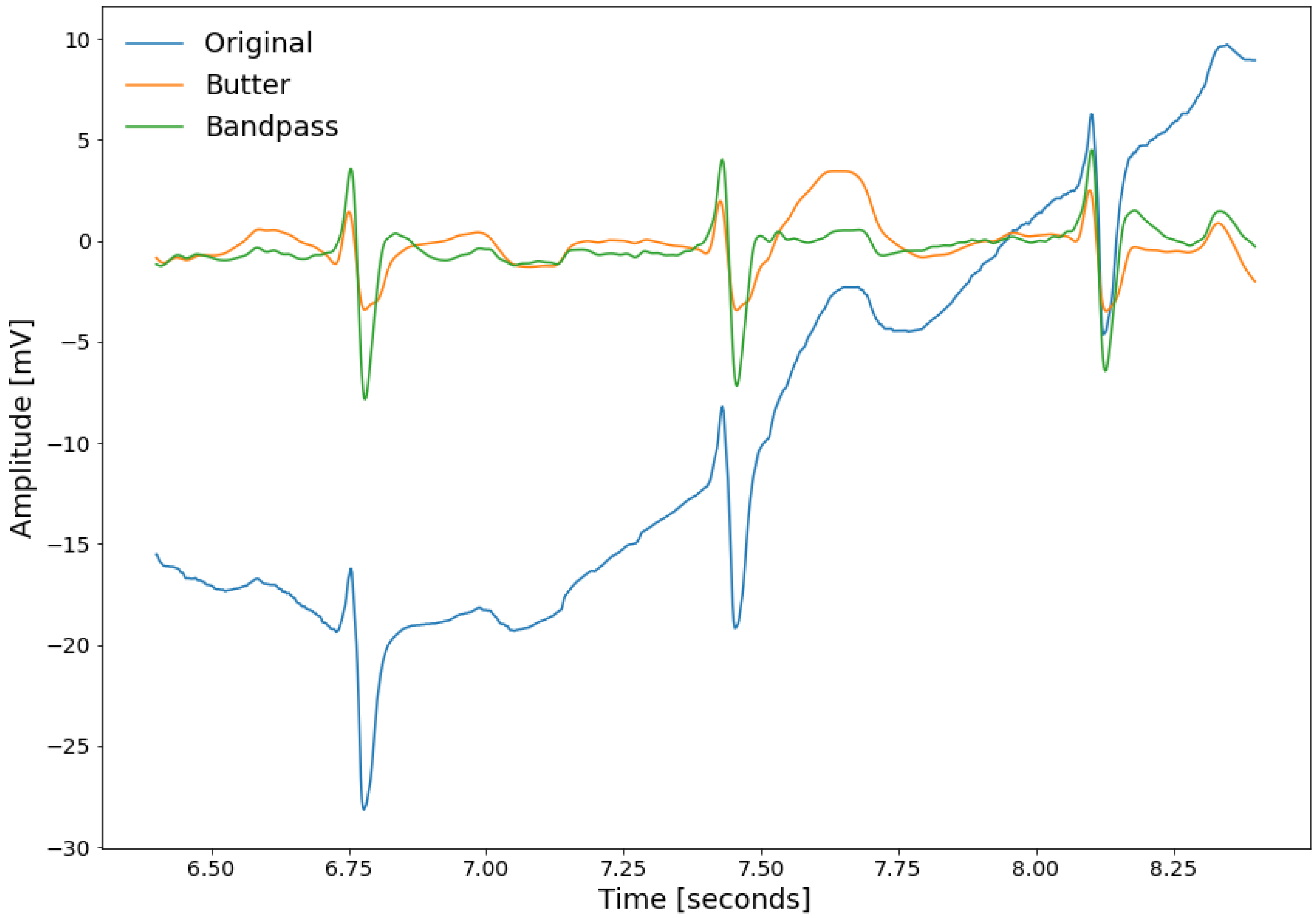
B a n d p a s s



Bandpass Signal : Notice how both the Bandpass and the Butter signals do correct most of our initial problems. However, the Bandpass is creating a sort of double T wave or an elevation in the ST segment which did not seem to be present in the Original signal.

For humans, this might lead to an erroneous diagnosis. However, perhaps if all the registers undergo this transformation, then the machine will learn that that new elevation should not affect in it's dx criteria.

Bandpass



Bandpass Signal : If we take a look at a different segment of the signal, specially between 7.5 and 7.75 seconds, we can see that the Original signal took a strange leap up.

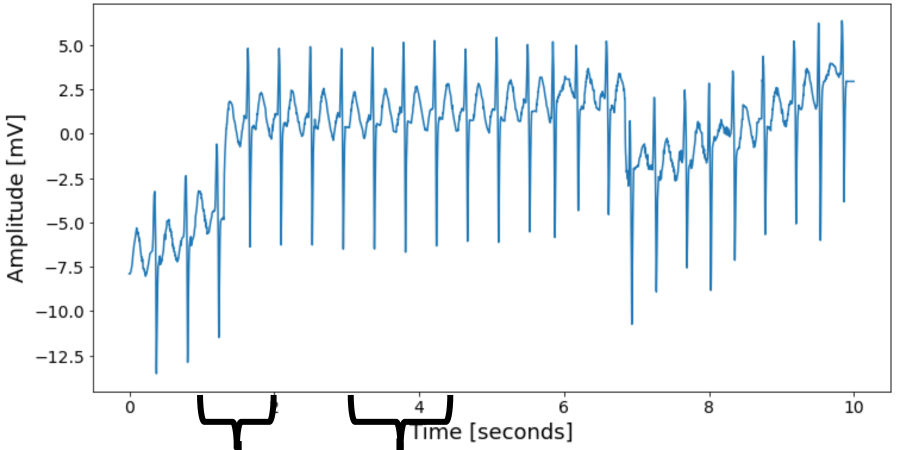
The Butter signal seems to have made a not so appropriate correction for it, since the QRS complex's peak is below the T wave.

On the other hand, the Bandpass filter does seem to convey the correct way in which the signal should behave, except for the ST elevations.

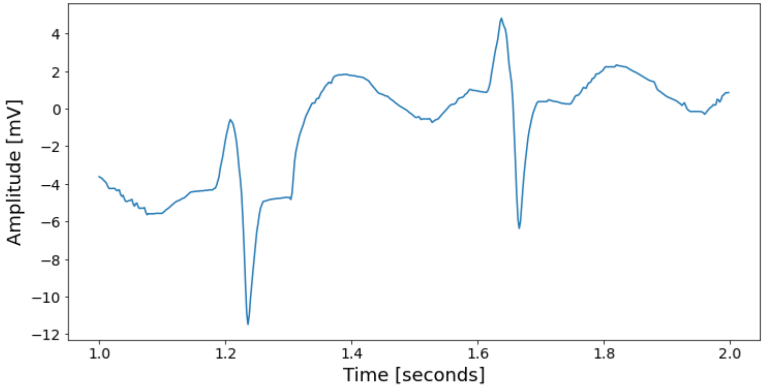
Pros and Cons

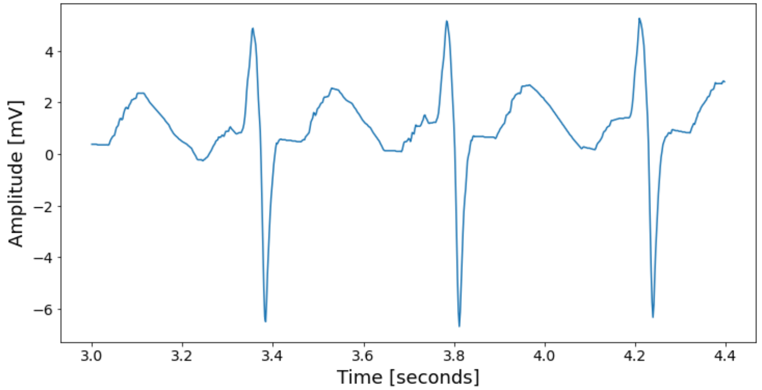
	Pros	Cons
Own Methodology (Smooth -> Quantiles -> Butter)	• When correctly parametrized, it seems to retrieve a very accurate represantation of the signal • This can help medical experts read the corrected signals and interpret them accurately	• **Still needs to be automatically parametrized (4 parameters)** • Slower • If it is not adequately parametrized, it produces some erroneous results • It sometimes flattens very extreme outliers
#1 Team (Bandpass)	• Retrieves a very uniform represantation of the signal • Faster • Does not require that much calibration of parameters (only 2 and we can use the ones the team used)	• There are signals which still seem to show outliers • There are “added” patterns (like the ST segment elevation seen previously) which could (or maybe not) affect model performance • Several “regular” signals are not so well reconstructed

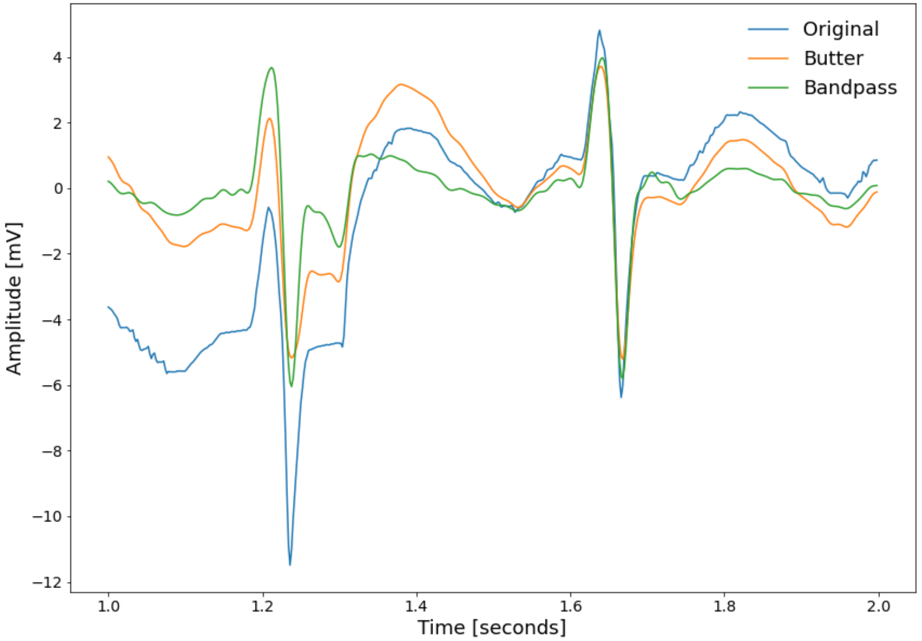
Example #1 with clear outliers

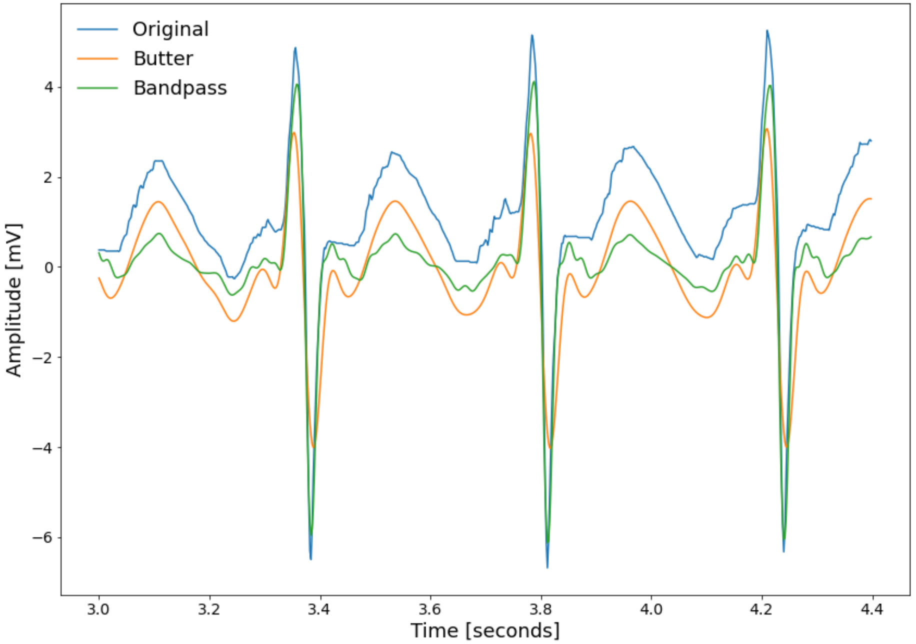


No clear winner. Butter seems to not be fitting well when there are steep changes, and Bandpass seems to be generating additional ST elevations.

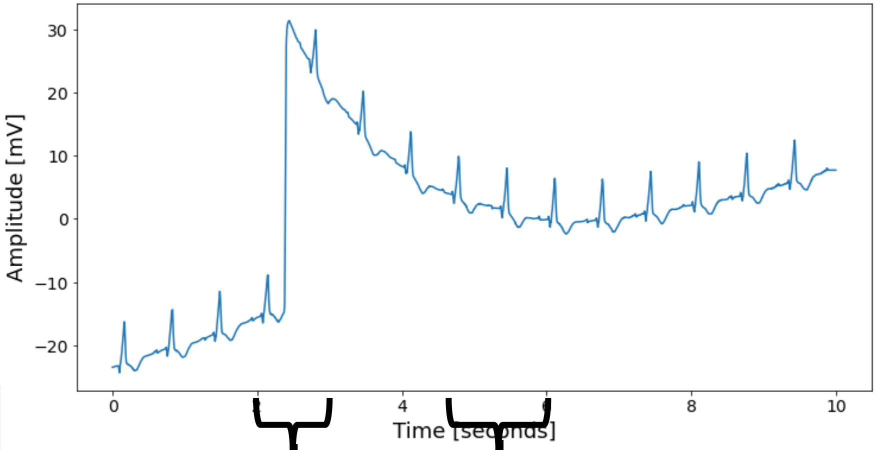




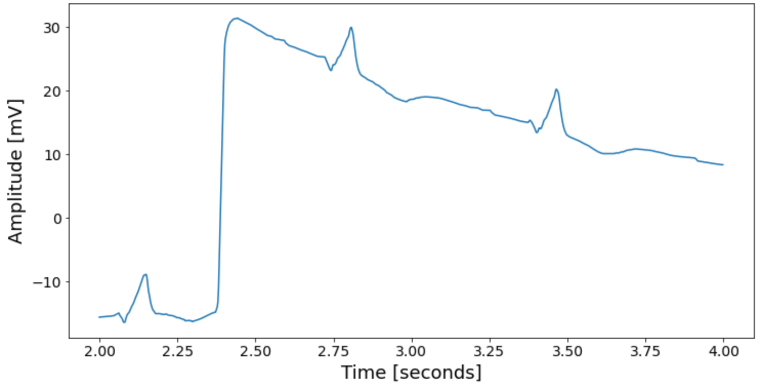


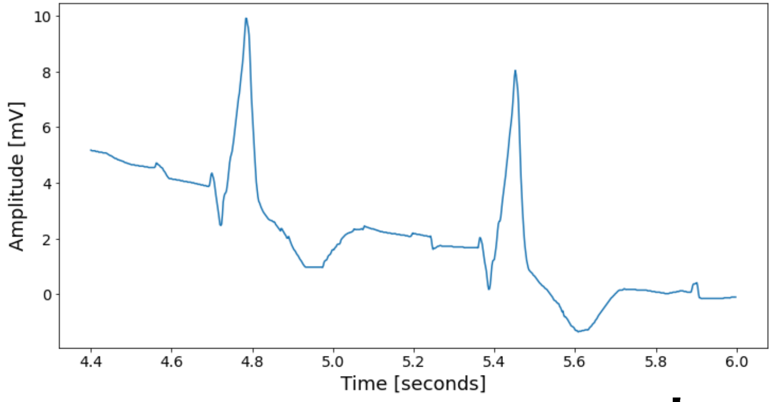


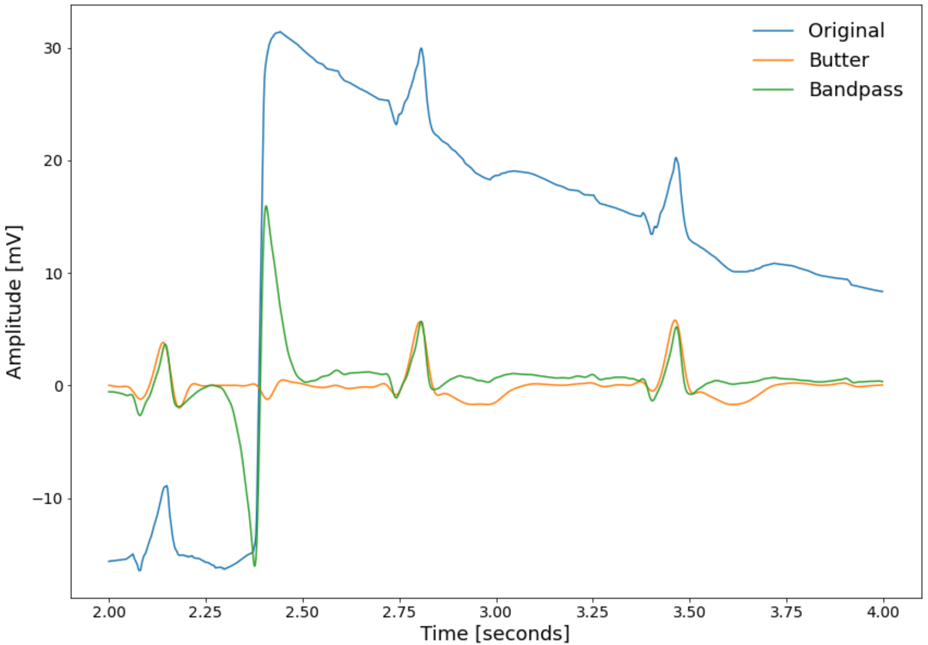
Example #2 with clear outliers

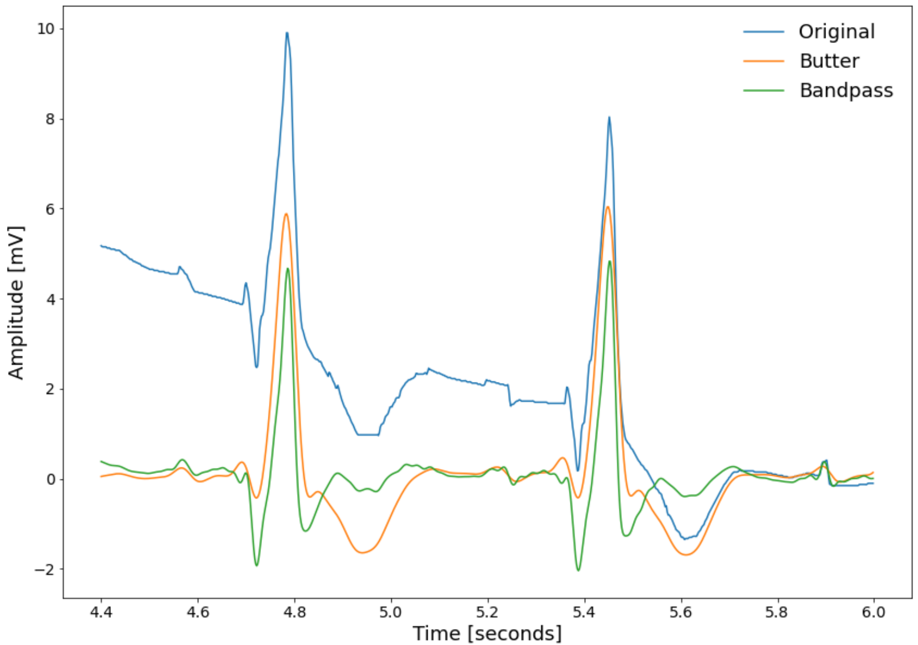


Butter seems better. Bandpass can't seem to feet well to very steep outliers. Also, it doesn't seem to capture the ST down-slope.



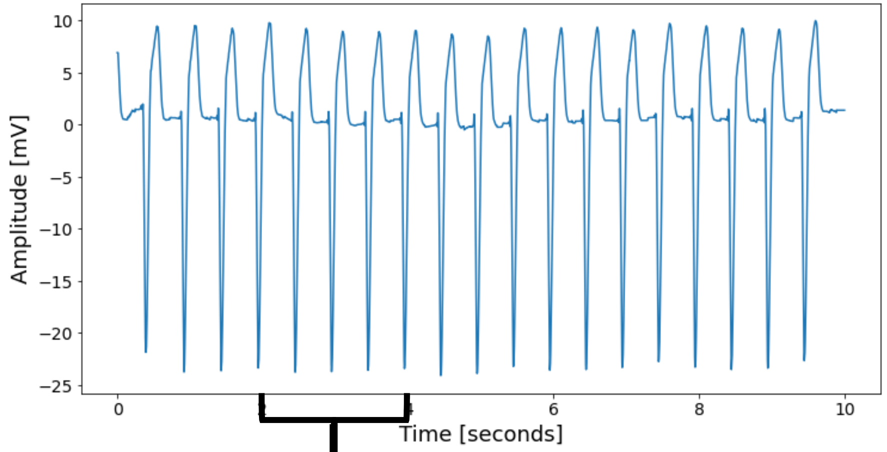


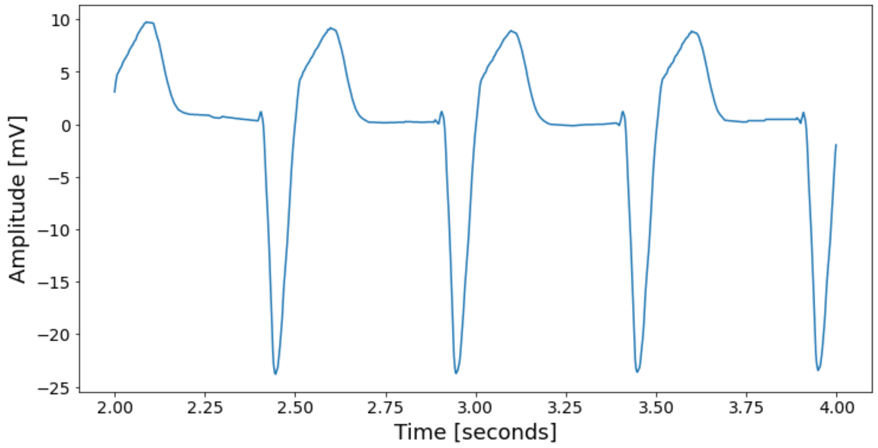


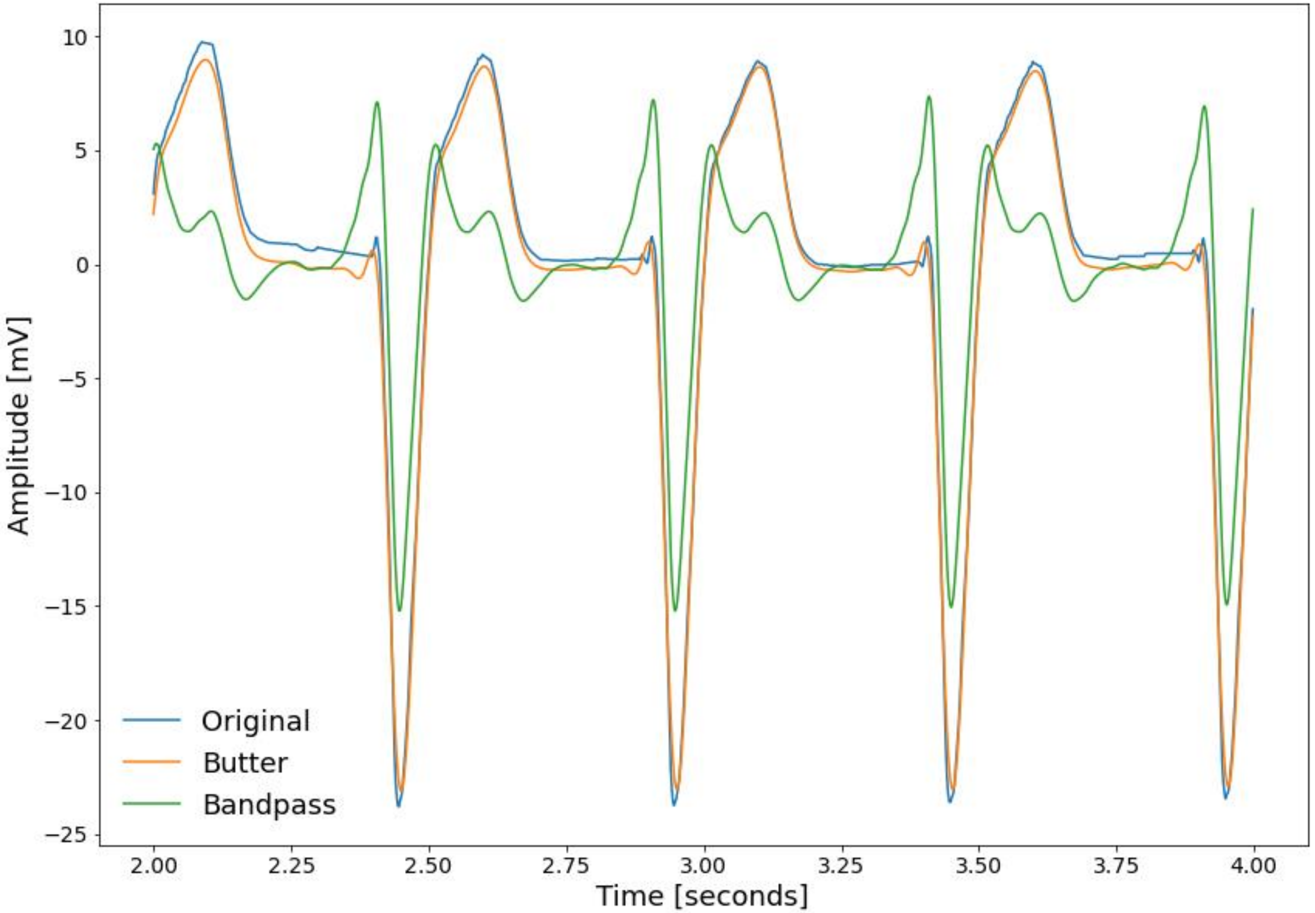


Example #1 without clear outliers

Butter seems better. Bandpass can’t seem to correctly follow the original signal in several instances. However, as mentioned before, there exists a chance for the computer to, having deleted certain frequencies, understand diagnoses in a different way from humans.

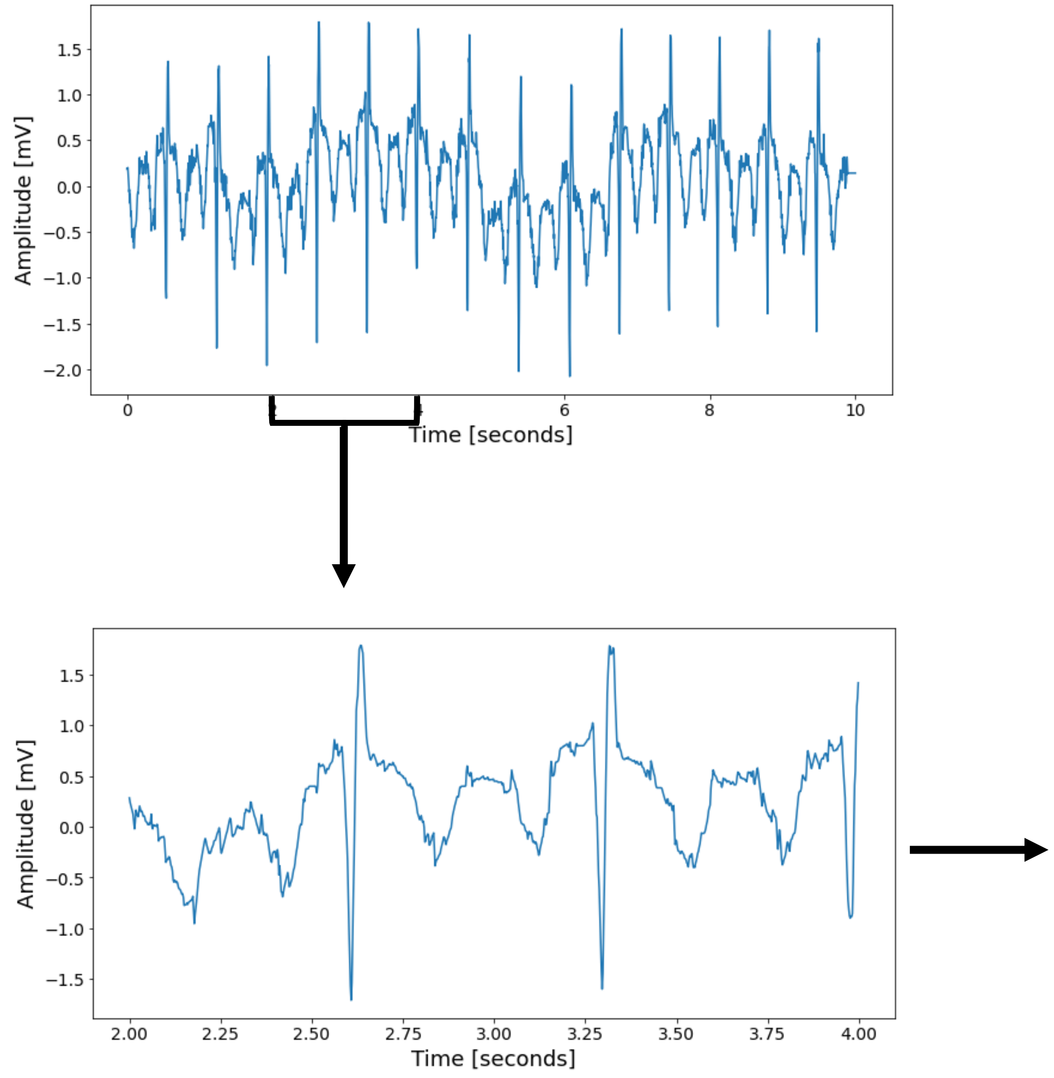


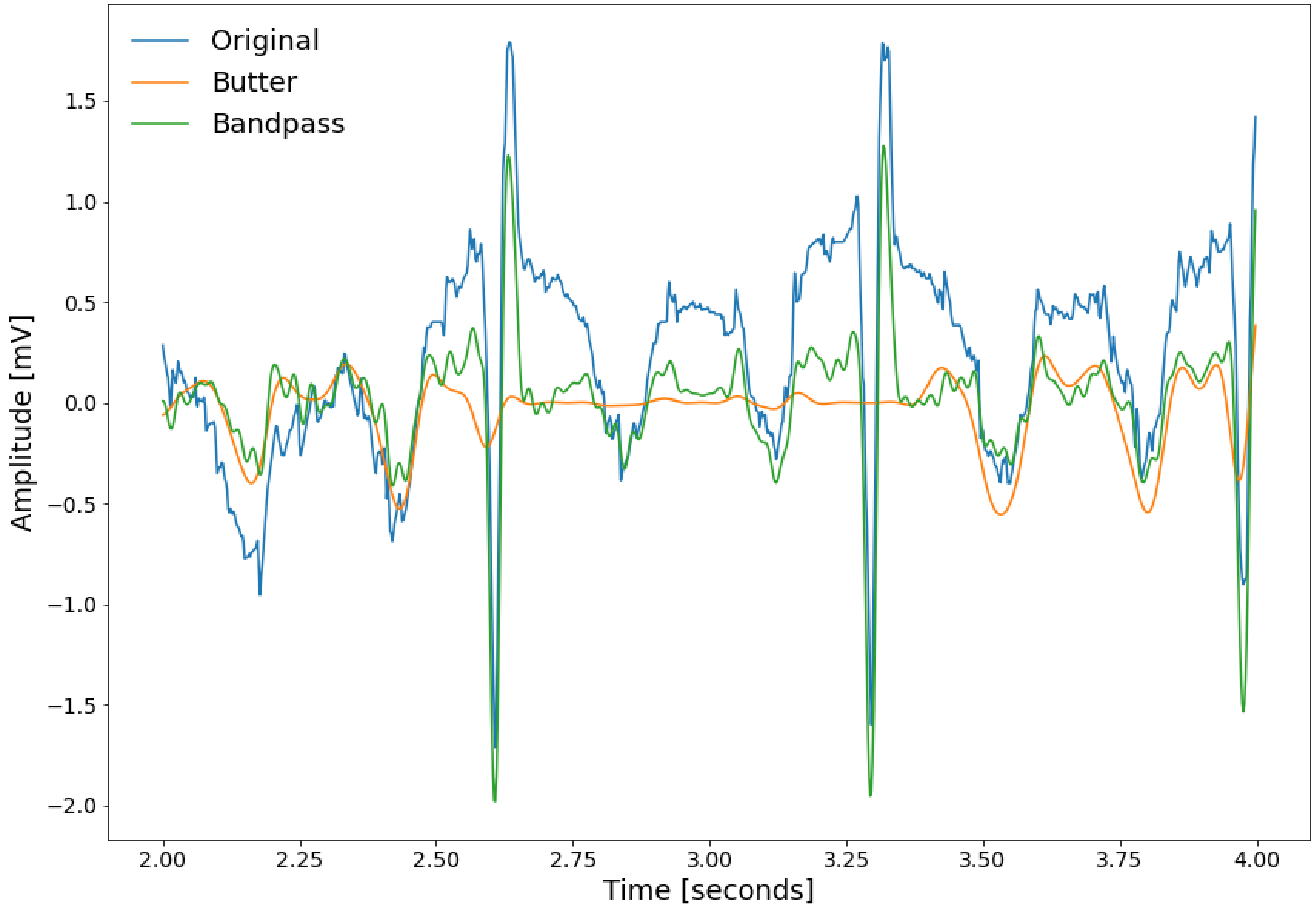




Example #2 without clear outliers

Bandpass seems better. This is an intentionally non-well parametrized example that shows how our own methodology can fail if the parameters are not well calibrated. See how it just flattens certain segments. This is just to show that we need to find the correct criteria to automatically generate the parmeters, or else we might lose information.





Summary

- Both our own and the #1 team methodologies to clean data have pros and cons.

- If we were to overcome the cons in our own methodology (namely automatically generate the parameters), then it seems to more accurately adjust the signals. This is positive in 2 ways:

  - The model will recieve well cleaned data
  - The cleaned data will be able to be interpreted and revised by any medical profesional, since we would be recovering the signal with minimal loss of information.

- Nonetheless, even if the #1 team methodology doesn’t accurately fit in some instances, it does not imply that the machine will not interpret the signals and their diagnoses in its own way.

  - In this case, the cleaned data might not be able to be accurately read by medical professionals since there is considerable more loss of information (for a human eye).

Proposed Next Steps

- Try the #1 team methodology since it is faster and already calibrated, get the results and compare them with the previous ones.

- Calibrate our own methodology, get the results and compare them with the #1 team ones.

  - For this, we might need to have signals be revised by medical experts.

  - The mistakes between the original and the corrected signals are to be recorded so that we can further improve on the automatization of the parameters.

  - This process might be iterative, so that after an initial batch of 50 has been annotated and then correctly tuned, another batch of 50 will be processed with the automatized parameters, and again passed to the medical team to be revised.

  - We consider 2-3 iterations might be enough to calibrate the parameters.

Questions

Smooth

- The biggest issue with the Smooth step is that it can set to 0 certain very noisy segments of the signal. We believe (without medical expertise) that most diagnoses are generally detected given that they are repetitive, so that even if one segment is erroneous, all the other ones should be able to accurately predict the dx.
- Even so, what is worse? To have segments be 0 or to have a noisy spike in them? In terms of how the model works, we believe it is best to set them to 0, but given my lack of medical knowledge we cannot be certain of this.

Quantiles

- Does using a threshold for cutting given lower and upper quantiles reduce information? Because some high and low peaks might be due to diagnoses related causes, and others might be due to noisy spikes given the electrical signal recording.
- Given these, how and when could we set appropriate boundaries? This might be more thoroughly answered through the iterative process of review.

Butter

- As seen in the examples, Butter reduces very small noise (in terms of amplitude). However, is this noise sometimes indicative of a diagnosis? For example, according to https://litfl.com/left-bundle-branch-block-lbbb-ecg-library/ , the left bundle branch block can be detected given a kind of double spike in some segments.
- I believe that for the most part, Butter won't affect this diagnosis since its smoothing is in smaller noises. However, are there diagnoses which can only be detected given even smaller patterns, that may indeed be affected by Butter smoothing?