OBSS - seminar 1
Robust Identification of Heartbeats with Blood Pressure Signals and Noise Detection (1.f)

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1   Introduction

As part of Seminar 1 in the course "Biomedical Signal and Image Processing", we attempted to implement and enhance the algorithm for detecting QRS complexes using BP complexes, as described in the paper *Robust Identification of Heartbeats with Blood Pressure Signals and Noise Detection*. The report presents the methodology from the article, our improvements, results, and potential avenues for future work.

2   Methodology

The algorithm itself is implemented in Matlab using the WFDB software package. As part of the project, a script was written to execute and evaluate the algorithm on data, the basis of which is taken from the example provided on the course website. All data used for implementation and evaluation is taken from the *set-p* directory of the website 2014 PhysioNet/CinC Challenge.

2.1   Preprocessing

No data preprocessing is included in the algorithm implementation. The reason for this is that the algorithm's performance relies on the functionality of the `gqrs` and `wabp` functions, which work very well on signals with a good signal-to-noise ratio [1].

2.2   Locating true QRS complexes

The process of locating true QRS complexes is comprised of multiple steps:

1. Extraction of QRS and BP complexes using WFDB's `gqrs` and `wabp` functions respectively.

2. Traversal of signal and analysis of multiple cases that can arise:

(a) Case 1: Only 1 QRS peak is sandwiched between 2 BP peaks.

(b) Case 2: More than 1 QRS peak is sandwiched between 2 BP peaks.

(c) Case 3: No QRS peak is sandwiched between 2 BP peaks.

2.2.1 Case 1 - 1 QRS, 2 BP

In this scenario, the analysis focuses on signals where precisely one QRS complex is situated between two consecutive BP complexes. This case is considered part of the 'clean' segment of the signal, implying a relatively noise-free interval. The following steps describe the processing logic for Case 1:

1. Ensure that the sliding window, used for computing the moving average, maintains a maximum size of 10 elements.

2. If the sliding window has fewer than 10 elements, add the current QRS complex between BP complexes to the window. Otherwise, update the sliding window by removing the oldest element and appending the current QRS complex.

3. Check if the sliding window is empty. If not, assess the distance between the current QRS complex and the next BP complex. If the distance is within the moving average add the QRS complex to the corrected signal. If the distance exceeds the moving average, subtract the moving average from the next BP complex, and add the result to the corrected signal, thereby predicting the true position of the QRS complex.

2.2.2 Case 2 - more than 1 QRS, 2 BP

In scenarios where two BP peaks encompass multiple QRS complexes, the authors of the paper proposed a solution involving a "simple horizontal line check" to detect true QRS complexes. Unfortunately, the methodology for this check is poorly explained, and as a result, it has not been implemented in this project. Instead, two alternative methods were explored to identify true QRS complexes.

The first (basic) method mirrors the approach used in Case 3. It predicts the position of the QRS complex by calculating the difference between the second BP complex and the current moving average.

The second method employs a temporal analysis approach to predict the most likely locations for the QRS complexes situated between the two BP peaks. The underlying concept is based on the assumption that these QRS complexes should be evenly spaced, allowing for a small deviation. To implement this, the following steps are taken:

1. Calculate the expected time interval based on the mean of differences between consecutive QRS complexes within the sliding window.

2. Set a threshold for acceptable deviation from the expected interval.

3. Identify true QRS complexes by evaluating the deviations from the currently evaluated interval. Those with deviations within the defined threshold are considered true detections.

While this approach leverages temporal analysis to refine the identification of true QRS complexes, considering the expected regularity in their temporal distribution, it is important to note that some aberrant heartbeats may be missed with this method.

2.2.3 Case 3 - no QRS, 2 BP

In the absence of a QRS complex between two consecutive BP peaks, Case 3 addresses scenarios where no discernible heartbeat is detected within this interval. The processing logic for this case is succinctly outlined below:

1. Check if the sliding window is not empty, ensuring that the algorithm is not at the beginning of the signal.

2. If the sliding window is not empty, subtract the moving average, calculated from the sliding window, from the next BP complex.

3. Add the resulting value to the corrected signal, incorporating the temporal adjustment derived from the moving average, thereby again predicting the true position of some QRS complex.

This approach accommodates situations where the absence of a QRS complex may be attributed to signal irregularities or variations in the physiological data. By considering the moving average, the algorithm adapts to changes in the signal characteristics, contributing to a more robust correction of the overall signal.

3 Results

The algorithm's results are obtained by evaluating two implementations: the basic algorithm implementation and the implementation using temporal analysis. The results of the basic implementation are presented in Table 1, while the results of the advanced implementation are shown in Table 2.

Analysis	Sensitivity	Positive Predictivity
Gross	98.97	99.85
Average	99.01	99.85

Table 1: Basic Implementation

In summary, the results indicate a slight improvement in positive predictivity when employing temporal analysis in cases where 2 BP complex sandwich

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Analysis	Sensitivity	Positive Predictivity
Gross	98.97	99.92
Average	99.00	99.92

Table 2: Temporal Analysis Implementation

more than 1 QRS complex, signifying that more QRS complexes are detected correctly, while the sensitivity remains the same. The results suggest that incorporating temporal analysis could positively contribute to the algorithm's performance.

4 Future work

Future work should focus on enhancing the robustness of the temporal analysis approach employed in this report. While initial results show promise, a more resilient algorithm is needed to address potential limitations, especially in identifying aberrant heartbeats or handling noisy signals. Fine-tuning the temporal analysis parameters and exploring advanced techniques, such as machine learning algorithms, could significantly improve the accuracy of QRS complex detection. Additionally, expanding the dataset to encompass diverse physiological variations would provide a more comprehensive evaluation of the algorithm's performance across various conditions.

References

[1] Bo Yang et al. "Robust identification of heartbeats with blood pressure signals and noise detection". In: *Computing in Cardiology 2014*. 2014, pp. 565–568.