Analysis of electrocardiographic (ECG) signals

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Abstract

This report introduces an implementation of the QRS detector featured in the paper titled Robust Detection of Heart Beats using Dynamic Thresholds and Moving Windows, which was presented as part of the PhysioNet challenge in 2014. The detector utilizes multiple signals, including ECG and BP, which undergo filtering with a trimmed moving average. Beats are detected on the range signal derived from local minimum and maximum values. The final step involves merging beats from selected signals into a unified sequence. When applied to the set-p database, also employed in the referenced paper, our implementation achieved an average sensitivity (SE) of 99.17% *and a positive predictivity (+P) of* 99.52%.

1 Introduction

In the first section of the course Biomedical Signal and Image Processing, we have been detecting heartbeats using ECG and pulsatile signals. In this report, we present our approach to reproducing the beats detector presented By Vollmer in *Robust Detection of Heart Beats using Dynamic Thresholds and Moving Windows* [1].

It was developed as part of the PhysioNet [2] and Computing in Cardiology Challenge 2014 on Robust Detection of Heart Beats in Multimodal Data [3]. Using some preprocessing, beats are detected using a *range* signal. Beats in all signals are detected using two configurations, one appropriate for ECG-like signals and the other for pulsatile signals. If beats using at least one configuration seem plausible, the merging step uses that signal. In this step, the delay of different signals is first corrected, because measuring devices had different distances to the hearth. Corrected beats of multiple signals are then merged into one sequence, depending on the number of signals that agree on them.

At the end there are two more steps - checking candidates of beats that were rejected in the previous step and building new multivariate subsets of signals. These two steps were not implemented in this assignment, yet similar accuracy on one database has been achieved.

We evaluated the implemented detector on all records from *set-p* and *training* databases that were provided as part of the mentioned challenge.

2 Methods

2.1 QRS detection

Preprocessing

The signal is first downsampled to $f_s = 80$ Hz to save on computation time. A centred **trimmed moving average** is then computed and subtracted from the signal itself, similar to a high-pass filter. The α%-trimmed moving average with window length w is calculated as

$$\text{TMA}_i = \frac{1}{w-2k} \sum_{j=k+1}^{w-k} \tilde{x}_j,$$

where $k = \lceil w\alpha/2 \rceil$ and $\tilde{x}$ is a sorted sequence of values in the window. Trimming value $\alpha = 25\%$ was used with $w_{\text{ECG}} = 0.2$ s and $w_{\text{BP}} = 1.0$ s for both configurations. The filtered signal is standardized to mean 0 and standard deviation 1. For beat extraction, the **range signal** is used. It is obtained by subtracting the local minimum from the local maximum in the neighbourhood of size $l_{\text{ECG}} = 0.2$ s or $l_{\text{BP}} = 0.4$ s. These are not computed centred around a point, but only for the times in the past.

Beat extraction

On top of the range signal, **smoothed** local minimum and maximum are computed using centred local minimum and maximum in the neighbourhood of size $l = 1.0$ s that were smoothed using moving average of length 80. An adaptive threshold is then used for beat position i:

$$r_i > 0.5(\text{SLmax}_i + \text{SLmin}_i) \text{ and}$$

$r_i = r_{i+1} = \ldots = r_{i+f_s/25}$ as a constancy criterion. New beat position is marked at index i if $r_{i-1} \leq 0.5(\text{SLmax}_i + \text{SLmin}_i)$ and parts for which $\text{SLmax} - \text{SLmin} \leq 0.4$ are marked as *noisy*.

Determine relevant channels

To determine if a channel is suitable for beat detection, the described beat extraction is run on a subset of length 30 s with both configurations. Distances RR between consecutive beats are calculated, as well as relative RR:

$$\mathrm{relRR}_i = \frac{\mathrm{RR}_{i+1}}{\mathrm{RR}_i}.$$

The channel is determined suitable with some configuration if

$$P(\mathrm{relRR} \in [0.8, 1.2]) \geq 80\%.$$

If both configurations are suitable, we use BP if the channel name contains any of strings *pressure, bp, cvp, pa, pap, art*, otherwise we use ECG configuration.

2.2 Multivariate combination

Dynamic delay correction

Every channel except the first one needs to be offset by some delay. For each beat we compute the distance to the closest beat in the first channel and then filter this sequence with a median filter with a window of length 19, i.e., approximately 20 s, as used in the paper.

Merging beats

After obtaining beats for all channels we merge them using a threshold 0.15 s. Beat needs to be present in every channel that was not noisy in this interval. The mean of these beats is then used for the final beat position.

3 Results

The described detector was evaluated on *set-p* and *training* databases that were provided with the challenge data. In Tables 1 and 2 we can see the best and worst 3 results from each database with respect to the F1 score.

The average sensitivity and positive predictivity of both databases are summarized in Table 3.

Record	SE	+P	F1
100	100.00%	100.00%	1.0
176	100.00%	100.00%	1.0
134	100.00%	100.00%	1.0
⋮	⋮	⋮	⋮
113	93.38%	99.68%	0.96
149	94.91%	90.79%	0.93
118	76.95%	94.43%	0.85

Table 1: *Best and worst results on set-p database.*

Record	SE	+P	F1
1023	100.00%	100.00%	1.0
2886	100.00%	100.00%	1.0
1003	99.90%	100.00%	0.99
⋮	⋮	⋮	⋮
2812	0.92%	0.92%	0.01
41173	0.20%	0.20%	0.00
1033	0.00%	0.00%	/

Table 2: *Best and worst results on training database.*

Database	SE	+P
set-p	$99.17\% \pm 2.46\%$	$99.52\% \pm 1.18\%$
training	$79.69\% \pm 28.23\%$	$86.68\% \pm 25.44\%$

Table 3: *Average results on all records from both databases.*

4 Discussion

As we can see from all tables, the detector works well on at least some signals in both databases. Since the first database contains less noisy signals, the detector performs better more consistently. On the other hand, it performs worse on the second database, but still good on the best signals in it. Both summary metrics are worse, but they also have a higher uncertainty.

Comparing results to the reported results in the paper, we only achieved SE 0.72% and +P 0.41% worse on the set-p database. This difference could be due to some implementation differences, but we also have not implemented the last two steps of the original detector. Perhaps the detector would work better on the second database if we included them as well.

References

[1] Marcus Vollmer. "Robust detection of heart beats using dynamic thresholds and moving windows". In: *Computing in Cardiology 2014*. 2014, pp. 569–572.

[2] Ary L. Goldberger et al. "PhysioBank, PhysioToolkit, and PhysioNet". In: *Circulation* 101.23 (2000), e215–e220. DOI: `10.1161/01.CIR.101.23.e215`. eprint: `https://www.ahajournals.org/doi/pdf/10.1161/01.CIR.101.23.e215`. URL: `https://www.ahajournals.org/doi/abs/10.1161/01.CIR.101.23.e215`.

[3] George Moody, Benjamin Moody, and Ikaro Silva. "Robust detection of heart beats in multimodal data: The PhysioNet/Computing in Cardiology Challenge 2014". In: *Computing in Cardiology 2014*. 2014, pp. 549–552.