An assessment of algorithms to estimate respiratory rate from the ECG and PPG signals

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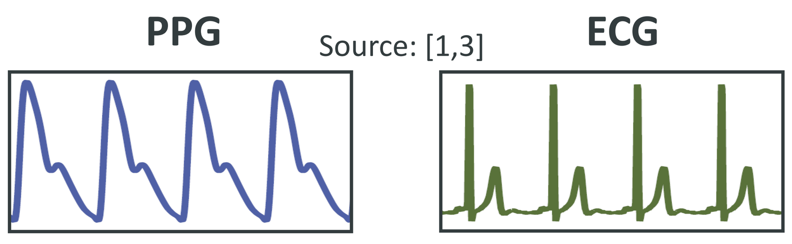
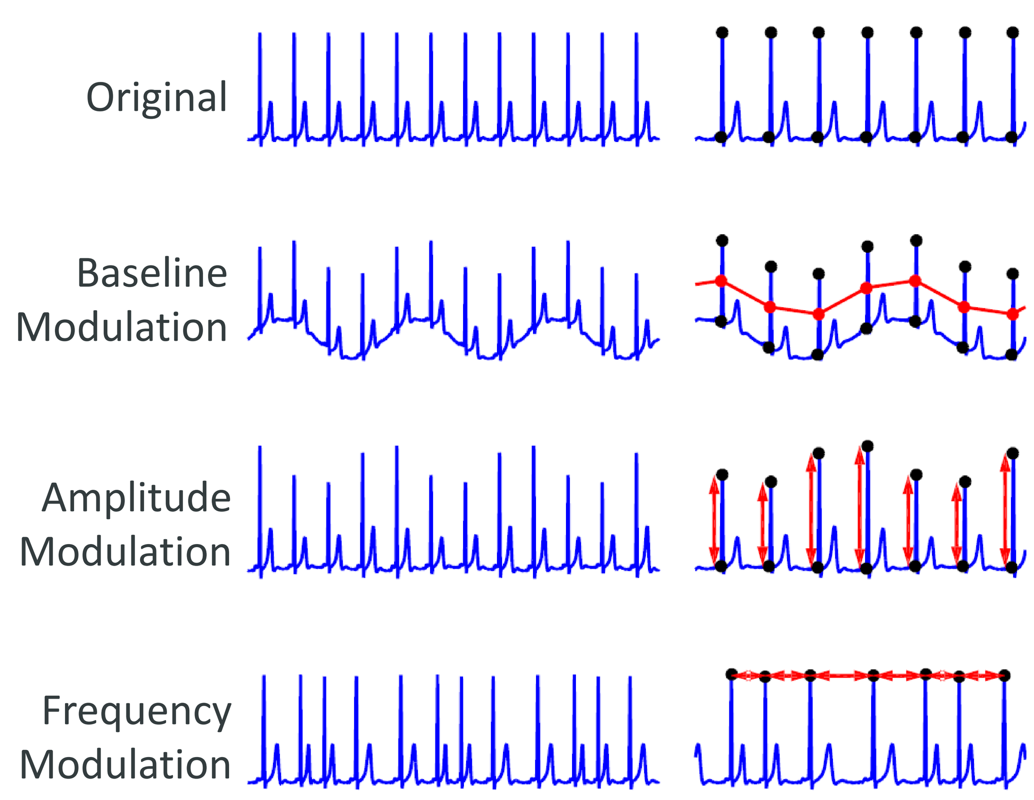
1. Estimating respiratory rate (RR) from the ECG and PPG

The importance of RR

Respiratory rate (RR, number of breaths per minute) is an informative indicator of physiological state. RR is used for diagnosing diseases such as pneumonia. It also changes in the hours before rapid deteriorations such as cardiac arrests, giving early warning. However, it is usually measured by hand. ECG and PPG signals may provide an alternative approach ...



The influence of respiration on the ECG and PPG



Respiration influences the ECG and PPG in three ways. This figure demonstrates extraction of the respiratory modulations of the ECG. Individual heart beats are detected (black dots). The three variations can then be extracted on a beat-by-beat basis.

Source: [2]

ECG and PPG signals

The electrocardiogram (ECG) and pulse oximetry (PPG) signals are widely measured in clinical practice to assess the state heart activity and blood oxygenation. They can also be measured continuously using wearable sensors:

Source: [3]

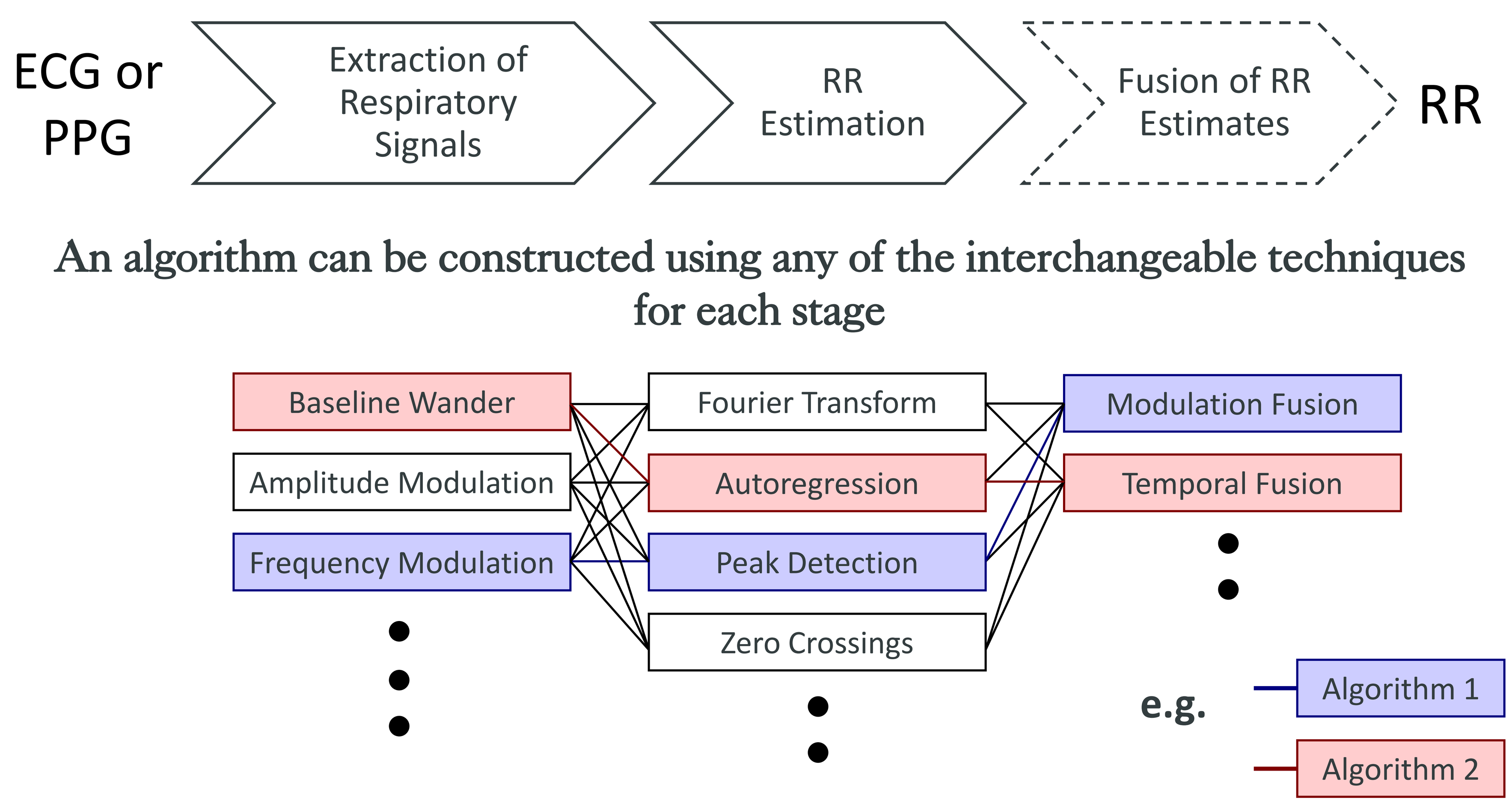
2. Assessment of respiratory rate algorithms

RR algorithms

Algorithms to estimate RR from the ECG or PPG consist of three stages (see right). Several techniques have been proposed for each stage. Consequently, over 100 algorithms – combinations of techniques – have been proposed. However, their performances have not been compared.

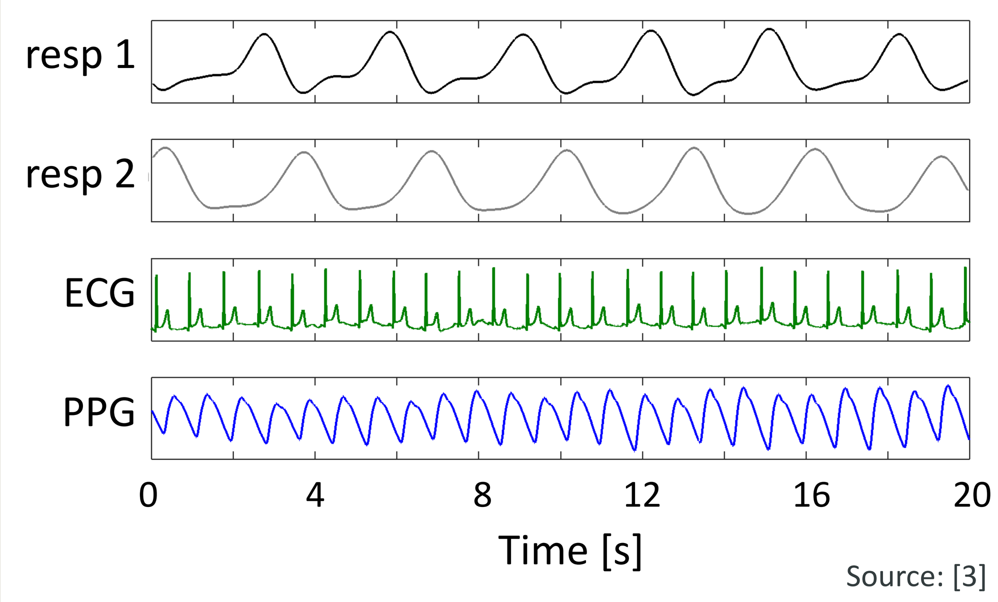
In this study we performed a comprehensive assessment of 314 algorithms. They were constructed by combining techniques from each of the three stages. Two examples are highlighted (see right).

The three fundamental stages of an RR algorithm



Dataset

We collected a benchmark dataset of ECG, PPG and reference respiratory signals from 39 young, healthy volunteers (see sample below). RRs were estimated from the ECG, PPG, and reference signals using 32 s windows of data.



Source: [3]

3. Results

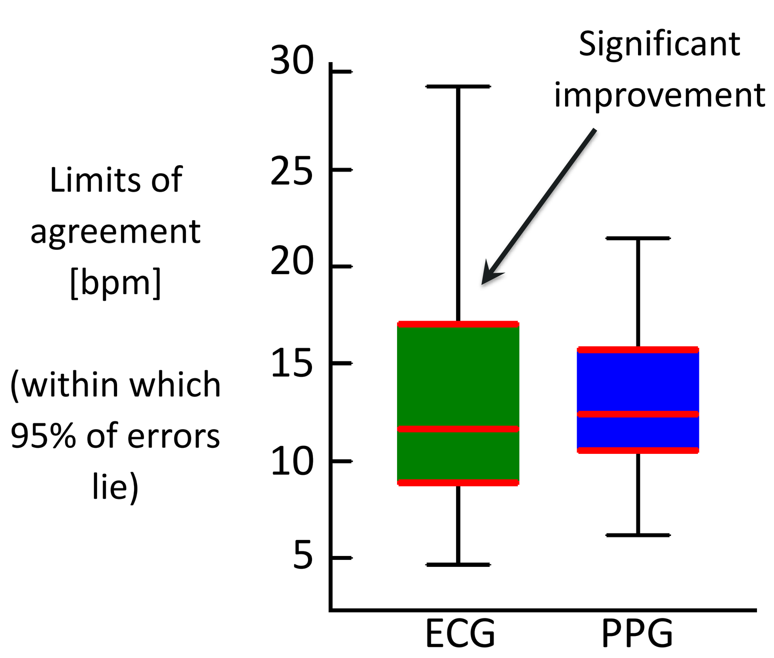
Algorithm performance

The best performance achieved when using the **ECG** was an error of 0.0 ± 4.7 breaths per min (bpm). This indicates a mean error of 0 bpm, and that 95% of the errors were less than 4.7 bpm. The best performance for the **PPG** was an error of 1.0 ± 6.2 bpm.

Both these results were achieved using algorithms which were novel combinations of techniques. Both algorithms fused RRs estimated simultaneously using each of the three types of respiratory modulation.

Comparison between ECG and PPG

The performance of algorithms improved slightly when using the ECG as an input rather than the PPG. However, performance was still reasonable with the PPG:



4. Relevance

Comparison to clinical practice

One of the reference respiratory signals acquired was an impedance pneumography signal, which is commonly used to monitor RR in critical care. It provided a performance of -0.2 ± 5.4 bpm, slightly worse than the best algorithm.

Therefore, the best algorithms may perform sufficiently well for clinical use. However, this assessment was conducted in ideal conditions, with young healthy subjects. Therefore, we are now assessing the performance of algorithms in the clinical setting to see if these conclusions hold.

Equipping future researchers

Both the algorithms and the benchmark dataset used in this study are publicly available at:

http://peterhcharlton.github.io/RRest

Accompanying Paper

Charlton P.H. and Bonnici T. et al. An assessment of algorithms to estimate respiratory rate from the electrocardiogram and photoplethysmogram, Physiological Measurement, 37(4), 2016, CC BY 3.0. DOI: 10.1088/0967-3334/37/4/610

References

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[3] Charlton P.H. The Processes and Benefits of Sharing Clinical Data. CC BY 4.0. DOI: 10.5281/zenodo.166546

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