RR algorithm validation using the simulated PPG signals

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I. Objective

1) To validate the RR algorithms by applying them to the simulated PPG signals.

II. Simulated datasets

In this report, I present the RR estimation results when applying simulated finger PPG datasets to our RR algorithms. These synthetic datasets have been prepared by Peter Charlton. It can be accessed from peterhcharlton.github.io/RRest. Each simulated data consists of 21 s recording of ECG and PPG, sampled at 500 Hz. The reference of the respiration for each simulated data is also included. The reference is not a signal but showing in time domain when breathing happens. There are a total of 192 data. The data are equally divided into 64 data for baseline wander, amplitude and frequency modulation, respectively.

A. *RIIV*

For data 1∼29 and data 88∼122, they have been labelled as baseline wander modulation. Respiratory-induced intensity variation algorithm provides the results for the respiratory signal. From the observation, 52 out of 64 data (81.3%) shows accurate RR estimation result compared to the reference breathing data provided by the datasets. The example of good and no-good extractions are shown in Fig.1 and Fig.2. The top graphs are the raw PPG data which shows the peak and onset detections in red and green, respectively. The red marks on the other graphs show the breathing points. All the estimated graphs are shown in the link of Table I. From the respiratory signal result as shown in Fig.1, this raw PPG signal has BW, AM and FM. In Fig.2, it shows that the reference RR is 40 breath per min. Eventhough the peaks and onsets are detected correctly the algorithms used are unable to show the respiratory signal, which in this data 258, the estimated RR is less than half of the reference RR.

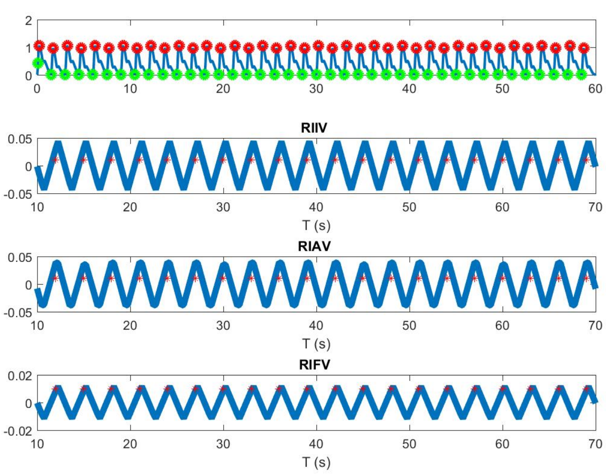


Fig. 1. Example of good RR estimation (data 90)

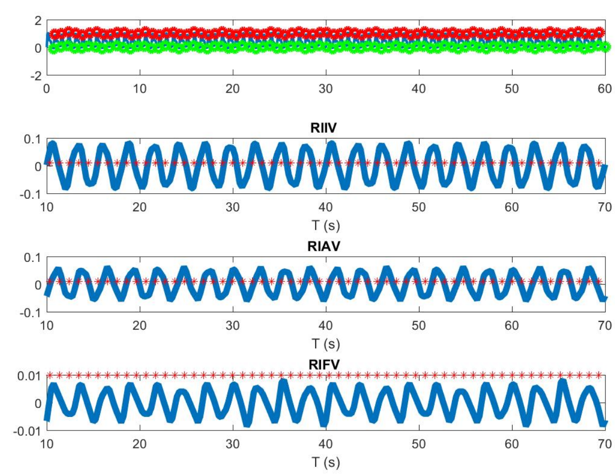
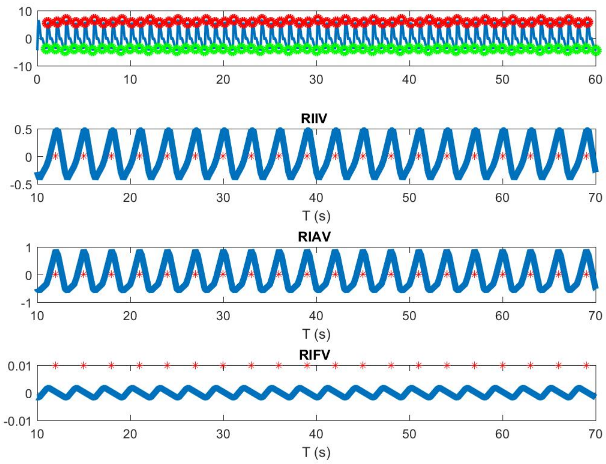


Fig. 2. Example of a no good RR estimation (data 258)

B. *RIAV*

For data 30∼58 and data 123∼157, they have been labelled as amplitude modulation. The example of good and no good extraction are shown in Fig.3 and Fig.4. As shown in Fig.3, the RIIV and RIAV show consistent rspiratory signals. This raw PPG data have BW and AM. Similar to RIIV, from the observation, when the frequency of the reference RR increase, the estimation becomes less effective.



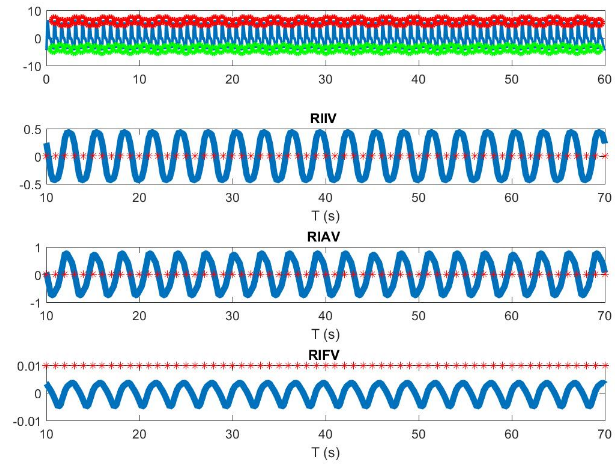


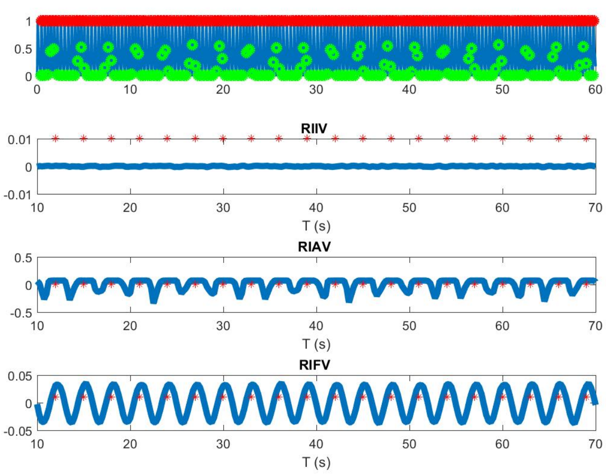
Fig. 3. Example of good RR estimation (data 129) Fig. 4. Example of a no good RR estimation (data 58)

TABLE I
SUMMARY OF RR ESTIMATION USING SIMULATED PPG SIGNAL

Modulation	Baseline Wander	Amplitude Modulation	Frequency Modulation
Simulated Data Number	1-29, 88-122	30-58, 123-157	59-87, 158-192
Good Estimation Data	52/64 (81.3%	53/64 (82.8%)	52/64 (81.2%)
Good Estimation Graph	BW Good	AM Good	FM Good
NG Estimation Graph	BW NG	AM NG	FM NG

C. RIFV

For data 59∼87 and data 158∼192, they have been labelled as frequency modulation. The example of good and bad extraction are shown in Fig.5 and Fig.6. In Fig.5, the raw PPG signals have FM and AM, less BW. For Fig.6, the estimation again becoming less effective when the frequency of reference RR increased. Hovewer, the RIFV algorithm is still providing the respiratory signal from the frequency variations of the PPG data.



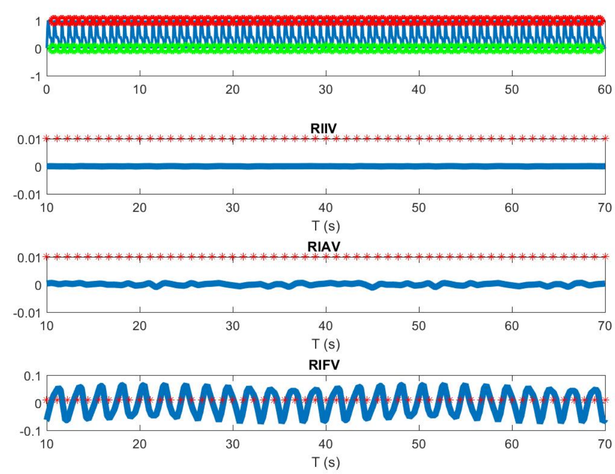


Fig. 5. Example of good RR estimation (data 185) Fig. 6. Example of a no good RR estimation (data 84)

III. CONCLUSION

From the analysis, it could be said that the current RR algorithm are able to estimate RR from finger PPG ∼80% of the results are good.