

Electrocardiogram-Derived Respiration using Dynamic Filter Coefficients

Saif Ahmad, Izmail Batkin, Owen Kelly, *Member, IEEE*, Miodrag Bolic, *Senior Member, IEEE*, Voicu Groza, *Fellow, IEEE*, Hilmi R. Dajani, *Senior Member, IEEE*

Abstract— A novel method employing dynamic band-pass filtering for extracting respiratory parameters from electrocardiogram (ECG) R-peak interval, height, and area is proposed with promising results (MAPE = 7% for breathing rate).

I. INTRODUCTION

Respiration is an important physiological signal. Common methods employed to measure respiration include capnograph, nasal airflow, elastic chest belts, and bio-impedance. However, problems such as artifacts/noise, high power consumption, loss of data due to mucus build-up in tubing, and patient discomfort are often associated with the above methods.

A complementary technique proposed by researchers is based on extracting the respiration signal from an electrocardiogram (ECG) – popularly known as ECG-derived respiration (EDR) [1]-[3].

We propose a novel method for extracting respiration signals from ECG R-peak intervals, height, and area, based on using the slope sum function (SSF) [4] and building dynamic band-pass filters, with promising results.

II. METHOD

The main steps of the proposed algorithm are as follows: (1) Analyze data from beginning to end in windows of *size* two minutes and *step* of size one minute; (2) Identify ECG R-peaks and create RR interval, R-peak height, and QRS area series; (3) Augment peaks in series of (2) using SSF; (4) Find peaks in the SSF-augmented series using zero crossings and compute mean inter-breath interval (IBI) and standard deviation (SD) of IBI or IBI variability (*Iteration 1*); (5) Build band-pass filter coefficients for each window, based on mean IBI and IBI variability of *Iteration 1*, where $F_{\text{Min}} = 1/\{\text{Mean (IBI)} + 2*SD(\text{IBI})\}$ and $F_{\text{Max}} = 1/\{\text{Mean (IBI)} - 2*SD(\text{IBI})\}$; (6) Band-pass filter the series of (2) using dynamic filter coefficients of (5); (7) Find peaks in the band-pass filtered series of (6) using zero crossings and compute mean IBI and IBI variability (*Iteration 2*).

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S. Ahmad, I. Batkin, M. Bolic and V. Groza are with the School of Electrical Engineering and Computer Science, University of Ottawa, Ottawa, ON, K1N 6N5, Canada (e-mail: saahmad@site.uottawa.ca; vbatkin@rogers.com; mbolic@site.uottawa.ca; groza@site.uottawa.ca).

O. Kelly is with Biopeak Corporation, 4043 Carling Avenue, Ottawa, ON, K2K 2A4, Canada (okelly@biopeak.com).

H. Dajani is with the School of Electrical Engineering and Computer Science, University of Ottawa, Ottawa, ON, K1N 6N5, Canada (corresponding author; phone: 613-562-5800; fax: 613-562-5175; e-mail: hdajani@site.uottawa.ca).

To test the proposed algorithm, we undertook a study on the PhysioNet Fantasia database [5] from which ten subjects (N=10, Age Range: 21-85 yrs) were randomly chosen for analysis. First 2 h of data was analyzed for all subjects.

III. RESULTS

Best results are obtained for IBI derived from QRS area, whereby *Iteration 2* correlation with reference nasal airflow-derived IBI is 66% and mean absolute percentage error (MAPE) is 7%. Moreover, for IBI variability derived from QRS area, *Iteration 2* correlation with reference IBI variability is 60% and mean absolute difference (MAD) is 0.3 s. All correlations and errors in *Iteration 2* are better than those in *Iteration 1*.

Comparatively, our MAPE of 7% for IBI derived from QRS area is lower than some previously reported EDR-based IBI results which achieved a minimum MAPE of 17% [1].

IV. CONCLUSION

This is the first study in which a dynamic filtering approach based on employing the SSF is proposed for improving EDR. Moreover, this is the first study in which IBI variability (an important biomarker) has been robustly estimated from EDR.

Future work will involve using fusion of the three proposed techniques – EDR based on R-peak interval, height, and area – for further improving accuracy.

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