Multi physiological signs model to enhance accuracy of ECG peaks detection

A. Delrieu[1], M. Hoël[1], C.T. Phua[2] and G. Lissorgues[1]

[1]ESIEE-ESYCOM, Paris, France
[2]School of Engineering, Nanyang Polytechnic, Singapore

Abstract- Accurate R peaks detection in electrocardiogram (ECG) is an important process to assess the cardiovascular health of an individual (e.g. heart arrhythmia, heart rate variability, etc.). Many studies have presented various methods to detect R peaks in ECG using single physiological signal (i.e. ECG) and are highly subjective to the quality of the ECG signal. In this paper, an accurate R peaks detection algorithm is proposed based on the use of electro-mechanical physiological signals (i.e. ECG and photoplethysmography (PPG)). Concurrent processing of both ECG and PPG is able to reduce the need to have high quality ECG and allows the use of simple signal processing algorithms to identify the locations of R peaks in ECG signals. The flexibility of our method was demonstrated through concurrent implementation on a low cost platform (i.e. BeagleBone Black (BBB)) and FPGA platform (i.e. myRIO from National Instrument), achieving respective accuracy of 96% and 98%, using physiological signals acquired in real-time. The accuracy provided by our method is able to be applied on wearables and supports accurate real-time assessment of cardiovascular health.

Keywords- Electrocardiogram (ECG), QRS complex, R-peaks, Photoplethysmography (PPG).

I- INTRODUCTION

The electrocardiogram (ECG) is an important and well-studied biological signal used in multiple medical applications. ECG comprises of multiple features where most lifestyle application is focused on the detection of the R-peaks within the QRS complex. The ability to determine R-peak accurately is often required in R-R intervals analysis to determine ECG anomaly due to heart arrhythmia.

Many research had been conducted on methods to detect QRS complex[1-2-3]. The best known methods are the differentiation methods[4], digital filters[5-9], neural networks[10-12], filter banks[13], hidden Markov models[14], genetic algorithm[15] and maximum a posterior (MAP) estimator[16-17]. In the paper by Balda RA[18], they proposed the differentiator operator to detect QRS complex, and this method was later used by Ahlstrom and Tompkins[19], Friesen[20] and Tompkins[21] to develop methods that are able to determine the sensitivity of QRS complex to noise. Finally, methods based on the Hilbert transform[22-23-24] have the ability to distinguish between dominant peaks in signal among other peaks. Though these methods have shown good results, however they may fail in cases of low amplitude R wave.

An effective way to pre-process R-peaks generally requires the setting of a threshold value, which is manually fixed at the lowest value possible aiming at preventing the detection of P and T waves; and baseline noise. However, it is a challenge to determine a threshold value that fits the ECG signal due to baseline wondering, motion artefacts and variations in P and T waves. Xu and Li[25] have shown that using adaptive thresholding for automatic determining of threshold provides suitable results for the detection of R-peaks. However, this algorithm dependent on the quality of ECG signal acquired.

To-date, concurrent acquisition of ECG and photoplethysmography (PPG) has become possible. In this paper, an algorithm to automatically detect R-peaks in ECG with poor signal to noise ratio (SNR) through concurrent processing of ECG and PPG signals was developed. This algorithm was implemented onto low-cost embedded platforms to demonstrate accurate real-time ECG R-peaks detection.

II- METHODOLOGY

The algorithm developed in this paper is divided into 3 parts. The first part is the pre-processing of the raw ECG and PPG signals to remove environmental noise. The second part is to apply an adaptive threshold to detect dominant peaks in the pre-processed ECG and PPG signals. Finally, cross comparison of peaks detected in ECG and PPG signals is used to enhance the accuracy of R-peak detection in ECG.

A ECG and PPG signal acquisition

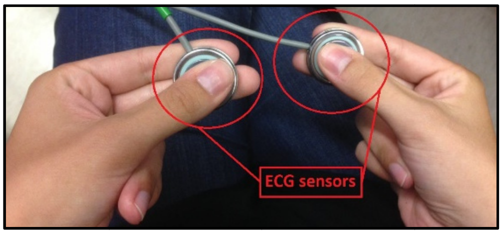
To acquire the ECG signal, commercially available Plessey's EPIC sensors were used. The sensors come in a pair and are used as dry electrodes held by each hand to

J. Goh et al. (eds.), *The 16th International Conference on Biomedical Engineering*,
IFMBE Proceedings 61,
DOI: 10.1007/978-981-10-4220-1_12

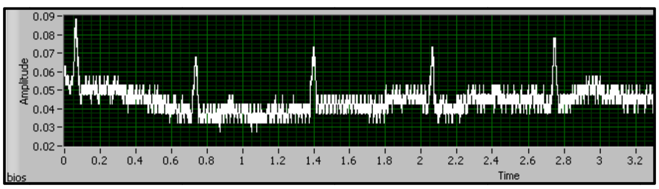
acquire ECG signal that is equivalent to Lead II in the traditional wet electrode ECG signal. The setup and typical waveform acquired is shown in Figure 1.

To acquire the PPG signal, commercially available Easy Pulse Sensor HRM-2511e was used and the waveform acquired is illustrated in Figure 2.

The ECG and PPG signals are concurrently digitised using the BeagleBone Black and myRIO from National Instrument.

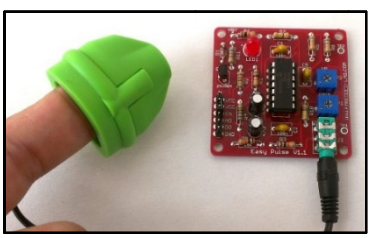


(a) EPIC sensors

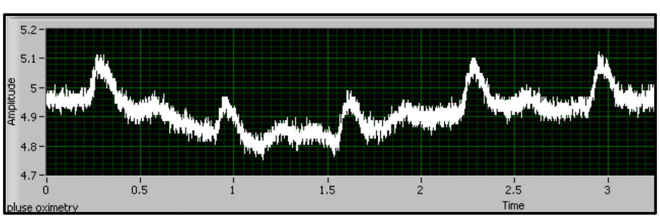


(b) Sample of ECG signal acquired

Figure 1. EPIC sensors for acquisition of ECG Lead II equivalent signals



(a) Easy Pulse Sensor



(b) Sample of PPG signal acquired

Figure 2. Easy Pulse sensors for acquisition of PPG equivalent signals

A. ECG and PPG pre-processing

Digital filters are used for the pre-processing of both ECG and PPG data as illustrated in Figure 3. The first filter is a 10th order infinite impulse response (IIR) filter with high pass filter with cut off frequency set at 0.5 Hz to eliminate low frequency noise. In the second filter, high frequency noises are removed by a low pass filter with cut off frequency set at 30 Hz. Finally, the last filter is a moving average filter used to reduce base-line wandering and smooth the ECG waveform for peak detection.

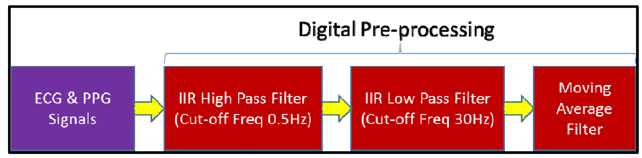


Figure 3. Digital Filtering of ECG and PPG signals

B. Adaptive threshold for peak detection

In both myRIO and BBB platforms, the threshold based peak detection function was used. The threshold value is originally set at half the supply voltage and is progressively reduced until the first peak is found. To achieve reliable peak detection, experiments were conducted to determine the optimal settings for the adaptive threshold voltage for peak detection. A cluster of five peak values were found to give repeatable and reliable peak detection. Equation 1 was derived based on these experiments and is used to determine the subsequent thresholds.

$$V_{threshold} = 0.7(V_{max}) - (2.776) * V_{std} \qquad \text{Equation 1}$$

where V_{max} = Maximum peak voltage from cluster of 5 peaks
V_{std} = Standard Deviation extracted from peak voltages

C. Cross comparison ECG vs PPG

Using the cardiovascular physiology that each of the cardiac cycle comprises an ECG followed by a PPG pulse, separated by a delay known as the pulse transit time (PTT), an algorithm is developed by cross comparing ECG and PPG peaks to enhance the accuracy of R-peak detection for ECG. For example, if an ECG peak is detected followed by the detection of a capillary pulse, the algorithm automatically identifies this as a valid ECG R-peak. If an ECG peak is not followed by a PPG peak, the algorithm automatically detects it as an extra ECG pulse which could possibly be a high T-wave detected by the adaptive threshold.

Through experimentations, it was found that a cluster of a five ECG and PPG peaks is able to give reliable and repeatable PTT. Equation 2 was derived from these experiments to define the lower and upper limits of PTT to differentiate ECG R-peaks from noise and artefacts.

$$Limits_{PTT} = Mean_{PTT} \pm (3.182/2) * Std_{PTT} \qquad \text{Equation 2}$$

where $Mean_{PTT}$ = Mean PTT from cluster of 5 peaks
Std_{PTT} = Standard Deviation PTT extracted from 5 peaks

III- RESULTS

The algorithm outlined above was implemented on both the BBB and myRIO platforms. Measurements were conducted on 6 volunteers where data were analysed in real-time and at the same time, stored. Post processing, using manual counting of peaks, was done to extract the accuracy of each implementations and the results are tabulated in Table 1 and Table 2.

Table 1. Measurement results using myRIO platform

Volunteer	Accuracy	Average accuracy
1	99%	98.6%
2	99%	
3	100%	
4	100%	
5	95%	
6	99%	

Table 2. Measurement results using BBB platform

Volunteer	Accuracy	Average accuracy
1	99%	96.5%
2	99%	
3	95%	
4	99%	
5	92%	
6	94%	

IV- CONCLUSIONS

Concurrent processing of both ECG and PPG is able to reduce the need to have high quality ECG and allows the use of simple signal processing algorithms to identify the locations of R peaks in ECG signals. This method is able to improve the accuracy in the detection of R-peaks in ECG with Signal to Noise Ratio (SNR) of 1-3dB, which is a challenge in existing methods due to the presence of noise; P and T-waves in ECG. The flexibility of our method was also demonstrated through concurrent implementation on a low cost platform (i.e. BeagleBone Black (BBB)) and FPGA platform (i.e. myRIO from National Instrument), achieving respective accuracy of 96% and 98%, using physiological signals acquired in real-time. The accuracy provided by our method is able to be applied on wearables and supports accurate real-time assessment of cardiovascular health.

V- ACKNOWLEDGEMENT

This research work is conducted at the Nanyang Polytechnic (NYP) of Singapore as part of the student exchange program between ESIEE, Paris and NYP, Singapore. The work is funded by the research grant from the Ministry of Education, Singapore.

REFERENCES

1. Xue Q, Hu YH, Tompkins WJ. Neural-network based adaptive matched filtering of QRS detection. IEEE Trans Biomed Eng. 1992;39:317–29.
2. Pan J, Tompkins WJ. A real-time QRS detection algorithm. IEEE Trans Biomed Eng. 1985;32:230–6.
3. Zhang F, Lian Y. QRS Detection based on multiscale mathematical morphology for wearable ECG devices in body area networks. IEEE Trans Biomed Circuits Syst. 2009;3:220–8.
4. Fraden J, Neumann MR. QRS wave detection. Med Biol Eng Comput. 1980;18:125–32.
5. Okada M. A digital filter for the QRS complex detection. IEEE Trans Biomed Eng. 1979;26:700–3.
6. Engelse WA, Zeelenberg C. IEEE Comput Cardiology. Long Beach, CA: IEEE Computer Society; 1979. A single scan algorithm for QRS detection and feature extraction; pp. 37–42.
7. Hamilton PS, Tompkins WJ. Quantitative investigation of QRS detection rules using the MIT/BIH arrhythmic database. IEEE Trans Biomed Eng. 1986;33:1157–65.

8. Keselbrener L, Keselbrener M, Akselrod S. Nonlinear high pass filter for R-wave detection in ECG signal. Med Eng Phys. 1997;19:481–4.
9. Suppappola S, Sun Y. Nonlinear transforms of ECG signals for digital QRS detection: A quantitative analysis. IEEE Trans Biomed Eng. 1994;41:397–400.
10. Dokur Z, Olmez T, Yazgan E, Ersoy OK. Detection of ECG waveforms by neural networks. Med Eng Phys. 1997;19:738–41.
11. Barro S, Fernandez-Delgado M, Vila-Sobrino JA, Regueiro CV, Sanchez E. Classifiying multichannel ECG patterns with an adaptive neural network. IEEE Eng Med Biol Mag. 1998;17:45–55.
12. Fernandez-Delgado M, Barro Ameneiro S. MART: A multichannel ART-based neural network. IEEE Trans Neural Netw. 1998;9:139–50.
13. Afonso VX, Tompkins WJ, Nguyen TQ, Luo S. ECG beat detection using filter banks. IEEE Trans Biomed Eng. 1999;46:192–202.
14. Coast DA, Stern RM, Cano GG, Briller SA. An approach to cardiac arrhythmia analysis using hidden Markov models. IEEE Trans Biomed Eng. 1990;37:826–36.
15. Poli R, Cagnoni S, Valli G. Genetic design of optimum linear and nonlinear QRS detectors. IEEE Trans Biomed Eng. 1995;42:1137–41.
16. Börjesson PO, Pahlm O, Sörnmo L, Nygårds ME. Adaptive QRS detection based on maximum a posteriori estimation. IEEE Trans Biomed Eng. 1982;29:341–51.
17. Sörnmo L, Pahlm O, Nygards M.-E. Adaptive QRS detection: A study of performance. IEEE Trans Biomed Eng. 1985;32:392–401.
18. Balda RA, Diller G, Deardorff E, Doue J, Hsieh P. The HP ECG analysis program. In: van Bemmel JH, Willems JL, editors. Trends in Computer processed Electrocardiograms. North Holland, Amsterdam, The Netherlands: 1977. pp. 197–205.
19. Ahlstrom ML, Tompkins WJ. Digital filter for real-time ECG signal processing using microprocessors. IEEE Trans Biomed Eng. 1985;32:708–13.
20. Friesen GM, Jannett TC, Jadallah MA, Yates SL, Quint SR, Nagle HT. A comparison of the noise sensitivity of nine QRS detection algorithms. IEEE Trans Biomed Eng. 1990;37:85–97.
21. Tompkins WJ. Biomedical digital signal processing. Upper Saddle River, NJ: Prentice-Hall; 1995.
22. Benitez DS, Gaydecki PA, Zaidi A, Fitzpatrick AP. A new QRS detection algorithm based on the Hilbert transform. Comput Card. 2000;1:379–82.
23. Chang WH, Lin KP, Tseng SY. ECG analysis based on Hilbert transform descriptor. IEEE Eng Med Biol Soc. 1988;1:36–7.
24. Chang AA, Chang WH. Hilbert transform and Fourier descriptors to ECG signal analysis. Proc IEEE Conf Eng Med Biol Soc. 1988;1:512–3.
25. Xu X, Liu Y. Adaptive threshold for QRS complex detection based on wavelet transform. 27th Annual Int. Conf Proc IEEE Eng Med Biol Soc. 2005;7:7281–4.