An Electrocardiogram (ECG) Signal Processing Algorithm for Heart Parameters Estimation based on QRS Complex Detection

Lorenzo Piazzo[1], Francesco Delli Priscoli[2], Guido Oddi[2], Donato Macone[1]and Silvano Mignanti[2]
[1]*Dipartimento di Ingegneria dell'Informazione, Elettronica e Telecomunicazioni, University of Rome "Sapienza", Rome, Italy*
[2]*Dipartimento di Ingegneria Informatica, Automatica e Gestionale, University of Rome "Sapienza", Rome, Italy*

Keywords: Signal Processing, ECG, QRS Complex Detection, Bravehealth.

Abstract: This paper presents an algorithm able to estimate heartbeat parameters, based on a QRS complex detection. The proposed algorithm demonstrates to be able to recognize heartbeat parameters even in highly noisy situations, i.e. where the ECG signal is extremely disturbed. Furthermore the algorithm was tested on real ECG signals generated by a so called *Wearable Unit*, a complex bio-signals sensor being developed by STMicroelectronics within the Bravehealth ICT FP7 EU funded project.

1 INTRODUCTION

Heart failures, strokes, anginas: there is a plethora of diseases a heart could suffer: up to now, patients affected by cardiovascular diseases were usually forced to continuously monitor their heart status going to hospitals for the usual, quite invasive, electrocardiography and similar analyses. The Bravehealth (ICT FP7 European Commission, under Grant Agreement no. 248694) project intended to be an advancement in this respect, developing a telemedicine system able to remotely monitor heart status of patients with cardiovascular diseases and, in case of abnormal situations, alert caregivers and patients with enriched information status.

In order to reach this challenging result a so called *Wearable Unit* (WU) has been developed in the framework of the Bravehealth Project: this unit consists in an extremely integrated system and is composed by several sensors (electrocardiogram – ECG, temperature, 3-axis motion, pulse-oximetry, etc.) in a "plaster" to be positioned on the chest of the patient in correspondence with the heart. Such a WU is not only designed to forward raw data to a remote management centre, but also to provide on-board pre-processing of the acquired signals, in order to pre-filter, pre-analyse and pre-process such a raw data (an interesting example could be to supply visual alerts directly on the unit itself).

This paper focuses on an approach for the estimation of heartbeat parameters, based on the QRS complex detection. The work reported was partially performed in cooperation with STMicroelectronics (STM) within the already mentioned Bravehealth project: a valuable contribution of this paper is to apply the proposed algorithm to real ECG signals produced by the WU. This paper is organized as follows. Section 2 reports a description of the typical ECG signal and an analysis of the state of the art about the QRS complex detection. Section 3 shows the proposed ECG signal processing chain. Section 4 illustrates the proposed QRS Detector Unit and Section 5 reports the results of the tests applied to real signals coming from the WU developed by STM. Brief conclusions are drawn in Section 6.

2 STATE OF THE ART

An electrocardiogram (ECG) signal is the expression of the myocardium electrical activity, measured on the body surface: it could be considered as a nearly periodic signal. The ECG signal contains a lot of information about heart status and possible diseases. In the medical tradition, the ECG signal cycle is labelled using alphabetical letters, namely the letters P, Q, R, S, and T for the individual peaks of the whole cycle waveform (see Figure 1). In the flagging step, diagnosis about heart status and possible diseases is usually performed based on features extracted from the timing and morphology

Piazzo L., Delli Priscoli F., Oddi G., Macone D. and Mignanti S..
An Electrocardiogram (ECG) Signal Processing Algorithm for Heart Parameters Estimation based on QRS Complex Detection.
DOI: 10.5220/0004209602490252
In *Proceedings of the International Conference on Biomedical Electronics and Devices* (BIODEVICES-2013), pages 249-252
ISBN: 978-989-8565-34-1

of the points indicated with those letters. The ECG signal analysis is crucial for the doctors to generate a correct clinical diagnosis (Kohler et al., 2002).

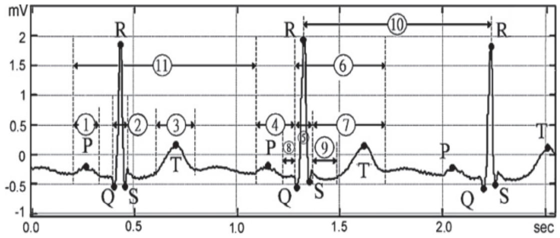

Figure 1: ECG waveform: (1) P wave; (2) QRS complex; (3) T wave; (4) PR interval; (5) QRS interval; (6) QT interval; (7) ST interval;(8) PR segment; (9) ST segment; (10) R–R interval (or beat); (11) cardiac cycle (including P wave, QRS complex, and T wave).

The QRS complex detection of ECG signal has been researched for the past four decades. According to the medical definition (Rangayyan, 2001); (Silipo et al., 1998), the most important information about ECG signal is almost concentrated on the P wave, the QRS complex and the T wave. These data include the positions and/or the magnitudes of PR interval, QRS interval, QT interval, ST interval, PR segment and ST segment (see Figure 1). In particular, QRS detection is quite difficult, since several issues might be present, such as noise, power-line interference, and the similarity between the T wave amplitude and the QRS complex. A lot of proposals of QRS complex detection algorithms, introducing solutions to the previously mentioned problems, have been investigated. For example, in (Pan et al., 1985), an algorithm (called PT method) is depicted, which recognizes QRS complex, through the analysis of positions and magnitudes of sharp waves using a digital band pass filter to reduce the false detection of ECG signals. In (Benitez et al., 2001); (Vijaya et al., 1998); (Keselbrener et al., 1997); (Dokur et al., 1997); (Afonso et al., 1999) digital filters were used to detect and classify ECG signal in time and frequency domains, while (Suarez et al., 2007) proposed a "Geometrical Matching Approach" to find the ECG beat. Finally, (Yeha et al., 2008) proposes a "Difference Operation Method" for detecting the QRS complex.

3 ECG SIGNAL PROCESSING

The proposed ECG signal processing chain is composed by three main units (as depicted in Figure 2): the flagging unit, the filtering unit and the QRS detection unit.

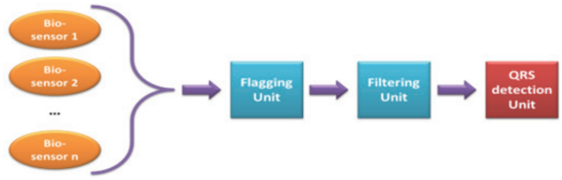

Figure 2: ECG signal processing chain.

In the flagging step, the input signal is analysed to detect corrupted parts, e.g. a saturated signal. The result of the analysis is a vector of signal flags that can be used by the rest of the processing steps. In the filtering step, a linear pass-band filter is applied to the signal. The filtering is carried out in the frequency domain by computing the Fast Fourier Transform (FFT) of the whole signal, by multiplication with the pass band response and taking the inverse FFT of the result. Finally, in the QRS detection step, the signal is analysed to identify and mark the peaks of the QRS complexes. Both the flagging and the filtering steps are quite standard and they will not be described in this paper. Instead, the core of the ECG processing, the QRS detection algorithm, will be described in the next Section.

4 QRS DETECTOR UNIT

The proposed detector is based on correlation: the detector can be seen as an adaptive matched filter detector. The algorithm maintains a correlation template of $2H+1$ samples, where $H = round(\hat{H}/F_s)$ and: (i) $round(.)$ means the rounding to the nearest integer operation; (ii) F_s is the sampling frequency; (iii) $\hat{H}$ is the template half length in sec. The template is denoted by t_i, for $i = -H, \dots, H$ and represents an estimate of the waveform segment centred on the QRS complex. The algorithm maintains an estimate of the current heart period, denoted by T_h, measured in samples.

Given the input ECG signal, denoted by x_n for $n = 1, \dots, N$, the detector produces a sequence of indices of estimated positions of the QRS peaks. The sequence of peaks positions is produced as follows. Given the position of the last identified QRS peak, denoted by P_m, the positions ranging from $P_i = P_m + round(0.5T_h)$ to $P_f = P_m + round(1.5T_h)$ are considered as candidate for the next peak. From each of these positions a signal segment of length $2H+1$ is extracted and the mean subtracted segment is correlated with the template. Formally, for the candidate in position J: (i) the segment is $s_i = x_{J+i}\ for\ i = -H, \dots, H$; (ii) the mean is $\overline{s} = (1/N) \cdot \sum_{i=-H}^{H} s_i$, and (iii) the correlation is $C = \sum_{i=-H}^{H} (s_i - \overline{s}) t_i$. The index of the candidate yielding the highest correlation, denoted by P_n, is selected as the new peak position and the corresponding segment, denoted by $s_i = x_{P_n+i}$ for $i = -H, \dots, H$ is stored. Every time that a new peak position P_n is produced by the correlation cycle just described, the following steps take place. The peak position is refined by setting P_n equal to the position of the maximum of the segment s_i and the segment is updated as $s_i = x_{P_n+i}$ for $i = -H, \dots, H$. This is done in order to lock the template center on the maximum of the QRS complex. Next, the template, the peak position and the heart period are updated according to the following equations:

$$t_i \leftarrow \lambda_i t_i + (1 - \lambda_i)(s_i - \overline{s}), i = -H, \dots, H \qquad (1)$$

$$T_i \leftarrow round[\lambda_T T_h + (1 - \lambda_T)(P_n - P_m)] \qquad (2)$$

$$P_m \leftarrow P_n \qquad (3)$$

where $\lambda_t = 0.7$ and $\lambda_T = 0.5$ are the forgetting coefficients. Finally, the newly produced T_h is checked against a minimum and a maximum value, T_{min} and T_{max}, and, if it is outside the range, it is set equal to the exceeded limit. Let us now discuss the algorithm initialization. This is accomplished by setting the first peak at the maximum of x_n for $n = H + 1, \dots, F_s$, i.e. the maximum of the first two seconds of the signal. The template is initialized to the signal segment of length $2H + 1$ centered on the first peak and the heart period is initialized to $T_h = 0.8F_s$. The procedure outlined above can get stuck on a false peak, lower than the QRS peak, especially when the template length is short. To avoid such aproblem it is sufficient to maintain and additional, longer template, representing the whole heartbeat. The beat template, denoted by τ_i for $i = 0,1, \dots,$ is initialized to zero and is updated at every beat detection, using the segment $\sigma_i = x_{P_{m+1}}$ for $i = 0,1, \dots, T_h$. The update rule is the following:

$$\tau_i \leftarrow \lambda_t \tau_i + (1 - \lambda_t)(\sigma_i - \overline{\sigma}), i \in [0, T_h - 1] \qquad (4)$$

and guarantees that the beat template has its peak in $i = 0$ as long as the QRS peak is correctly detected. When the algorithm is stuck to a lower peak, the maximum of the beat template will not be in $i = 0$ anymore. When this situation is detected, the last estimate is shifted in order to match the maximum of the beat template and the correlation template reinitialized. In conclusion, the algorithm is able to produce a sensible measure of the quality of the beat detection, namely the correlation coefficient between the template and the extracted signal segment. The computational complexity for processing an ECG file with N samples is easily evaluated to be $O(2HN)$ multiply-add operations.

5 RESULTS

The ECG processing chain was implemented in MATLAB and tested on two signals, produced by the Wearable Unit prototype. The two signals were selected as worst cases, being them affected by disturbances like power line interference and movements artifacts. The first signal was severely affected by power line disturbances and, by studying its spectral content, strong peaks were identified at frequencies as low as 22 Hz. Therefore the filter was selected as a band-pass filter with raising edge between 0.1 and 0.5 Hz and falling edge between 17 and 20 Hz. The rising and falling parts were a raised cosine junction. The template half window $\widehat{H}$ was set to 0.1 seconds. In the flagging step, the input signal is analysed to detect corruptions. The results for the first signal are reported in Figures 3, 4 and 5 where the first plot reports the original ECG, the second plot reports the filtered ECG, the QRS marks and the peaks envelope and the third plot reports the estimated heart period (in seconds) and the beat correlation coefficient. All signals are plotted versus the time in seconds.

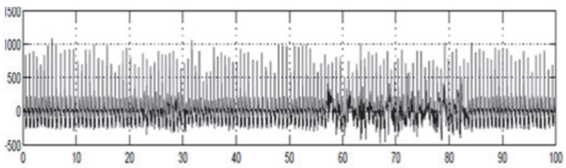

Figure 3: Original first ECG signal.

Observing this set of figures, the preprocessing is successful in limiting the power-line disturbance. The QRS peaks are correctly marked except around 30 seconds, were the noise is too high for a reliable detection, and 55 seconds, where the signal is absent (flagged due to saturation).

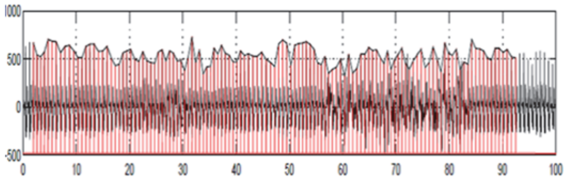

Figure 4: Filtered and marked first ECG signal.

However the peaks are correctly detected elsewhere. Furthermore, the unreliable peaks are identified by a lower correlation coefficient, with a zero correlation coefficient indicating flagged data or false maximum detection. The results for the second signal are reported in Figures 6, 7 and 8 and are quite similar (the QRS peaks are correctly identified).

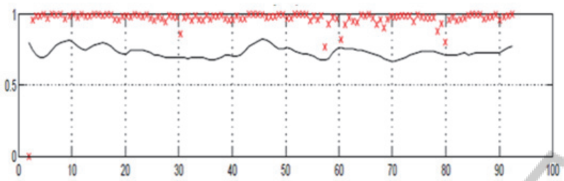

Figure 5: Estimated heart period (in seconds) and beat correlation coefficient of first ECG signal.

Since this signal is less noisy, the band-pass filtering could be skipped, since the QRS detection works fine even on the original, unfiltered, signal.

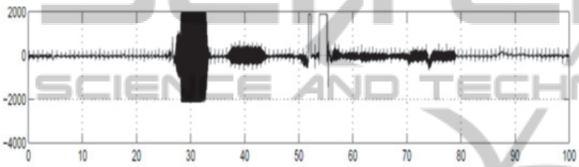

Figure 6: Original second ECG signal.

6 CONCLUSIONS

In this paper an approach for the estimation of heartbeat parameters is presented, based on a QRS complex detection. The QRS detection algorithm described in the paper demonstrates to behave very well even on the noisy ECG signals produced by the Wearable Unit. The algorithm results to be an optimal candidate for its deployment into the WU, after the phase of re-design of the algorithm for the firmware of the unit itself. Considering the trade-off between costs and benefits, a direct hardware implementation of the algorithm is envisaged.

DISCLAIMER

The work described in this paper is partially based on the results of the ICT FP7 Integrated Project Bravehealth. The Bravehealth consortium receives research funding from the European Community's FP7. Apart from this, the EC has no responsibility for the content of this paper. The information in this document is provided as is and no guarantee or warranty is given that the information is fit for any particular purpose. The user thereof uses the information at its sole risk and liability.

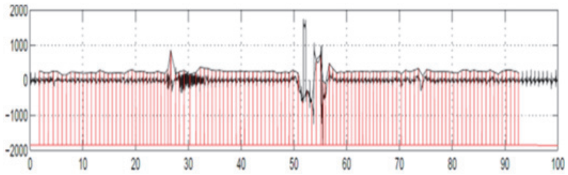

Figure 7: Filtered and marked second ECG signal.

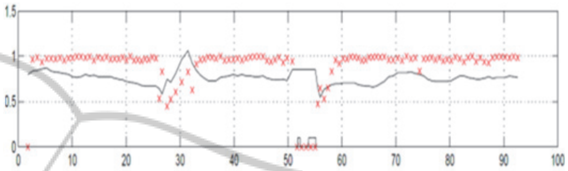

Figure 8: Estimated heart period (in seconds) and beat correlation coefficient of second ECG signal.

REFERENCES

Afonso V. X., Tomkins W. J., Nguyen T. Q., Luo S., 1999, ECG beat detection using filter banks, *IEEE Trans. Biomed. Eng.* 46 (2), pp. 192–202.

Benitez D., Gaydecki P.A., Zaidi A., Fitzpatrick A.P., 2001, The use of the Hilbert transform in ECG signal analysis, *Comput. Biol. Med.* 31, pp. 399–406.

Dokur Z., Olmez T., Yazgan E., Ersoy O. K., 1997, Detection of ECG waveforms by neural networks, *Med. Eng. Phys.* 19 (8), pp. 738–741.

Keselbrener L., Keselbrener M., Akselrod S., 1997, Nonlinear high pass filter for R-wave detection in ECG signal, *Med. Eng. Phys.* 19 (5), pp. 481–484.

Kohler B. U., Henning C., Orglmeister R., 2002, The Principles of Software QRS Detection, *IEEE Eng. Med. Biol.* 21 (1), pp. 42–57.

Pan J., Tompkins W. J., 1985, A real-time QRS detection algorithm, *IEEE Trans. Biomed. Eng. BME*-32 (3), pp. 230–236.

Rangayyan R. M., 2001, *Biomedical Signal Analysis: A Case-study Approach*, Wiley–Interscience, New York, pp. 18–28.

Silipo R., Marchesi C., 1998, Artificial neural networks for automatic ECG analysis, *IEEE Trans. Signal Process.* 46 (5), pp. 1417–1425.

Suarez K. V., Silva J. C., Berthoumieu Y., Gomis P., Najim M., 2007, ECG beat detection using a geometrical matching approach*, IEEE Trans. Biomed. Eng.* 54 (4), pp. 641–650.

Vijaya G., Kumar V., Verma H. K., 1998, ANN-based QRS-complex analysis of ECG, *J. Med. Eng. Technol.* 22 (4), pp. 160–167.

Yeha Y. C.,Wanga W. J., 2008, QRS complexes detection for ECG signal: The Difference Operation Method, *Computer Methods and Programs in Biomedicine* 91, pp. 245–25.