PHOTOPLETHYSMOGRAPHIC SENSOR FOR MOVING PERSON HEART RATE ESTIMATION

Darius Jegelevičius[1,2], Vaidotas Marozas[1,2], Arūnas Lukoševičius[1,2], Linas Svilainis[2]

[1]Biomedical engineering institute, Kaunas University of Technology, Kaunas, Lithuania
[2]Signal processing department, Kaunas University of Technology
Studentu str. 65-111, LT-51369, Kaunas, Lithuania
darius.jegelevicius@ktu.lt

[Selected from 3rd International Conference on Communications, Electromagnetics and Medical Applications (CEMA '08), Athens, Greece, 6-8 November 2008]

Abstract

Investigation of photoplethysmo-graphic (PPG) sensors application for subjects' heart rate monitoring for in-situ conditions is presented. Inertial acceleration sensor mounted together with PPG sensor was used for estimation of motion intensity. The sensor signal was acquired by placing it on the subject's: forehead, breastbone and wrist in the rest and active moving conditions. ECG sensor was used as a reference source. The most accurate results were obtained from the forehead. Analysis showed that time - frequency representation of PPG signal based heart rate is the superposition of two time - frequency representations: noise free heart rate signal and motion intensity signal. An application of recursive least squares adaptive filter to PPG signal showed encouraging results in terms of less interference components left in time - frequency representation of the heart rate.

1. Introduction

Photoplethysmographic (PPG) sensors [1] are widely used in monitoring of blood oxygenation and heart rate (HR) of the subjects in clinical bed rest conditions [2, 3]. When patient motion intensity is relatively low, there is a good correlation in heart rate between ECG and PPG signals. PPG sensors are attractive due to compactness, noninvasiveness and functionality. The PPG sensor has an advantage against the multielectrode ECG sensor, especially in telemedicine applications [4].

However subject movement introduces a large clutter into PPG signal. This paper is dedicated to present the investigation of PPG sensor application for moving person heart rate estimation.

2. Sensor electronics

An experimental infrared light sensor based on reflection was used for PPG signal registration (Figure 1).

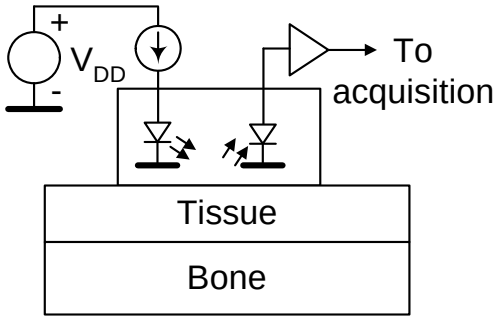

Figure 1. PPG sensor

Two TSMS3700 infrared LEDs with the excitation current 30 mA have been used to generate the luminous flux. The BPW34 photodiode was used for the reception. Signal was conditioned using operational amplifier AD8047. Motion intensity was estimated using two axes accelerometer ADXL202 with low pass filter (cut-off frequency 1kHz) mounted together with PPG sensor (Figure 2).

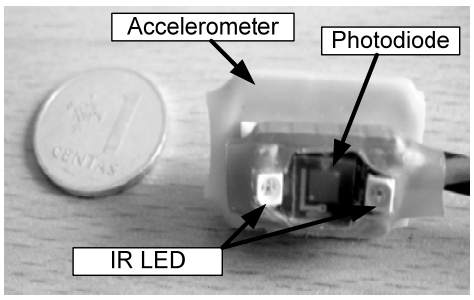

Figure 2. Combined placement of PPG and acceleration sensors

Inertial acceleration sensor fusion with PPG sensor ensures that acceleration data is collected at the same location.

3. Data collection

The PPG signal was acquired (Figure 3) by placing the sensor on the subject's: a) forehead, b) breastbone, c) wrist in the rest and active moving (walking, running, jumping and elliptical cross trainer) conditions. The ECG chest strap (Polar Oy) was used as the reference source of heart rate.

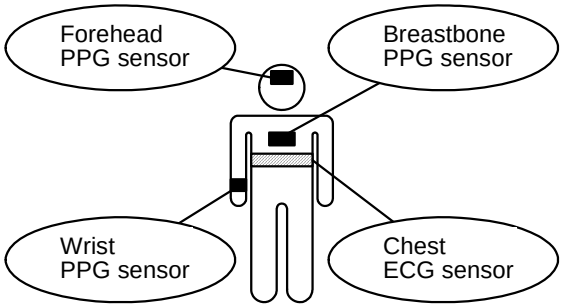

Figure 3. Sensor placement

PPG, acceleration and ECG signals were digitized (Figure 4) by using the biosignals' acquisition system MP35 from Biopack Inc.

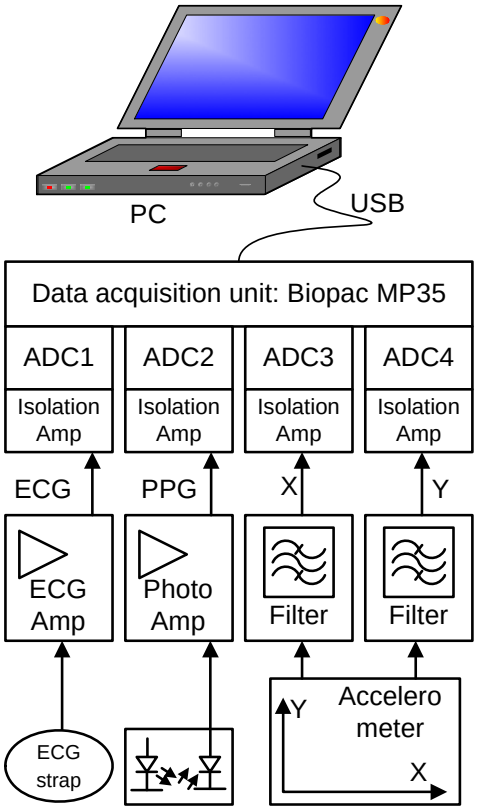

Figure 4. Acquisition system

It has four isolated, human-safe, universal biopotential or transducer input amplifiers with 24bit AD converters. The sampling rate was chosen to be 1kHz. High sampling rate ensures no short pulses coming from heart rate monitoring strap are missed. Raw signals were passed via USB interface to personal computer and stored for offline processing. Signal processing algorithms were developed in MATLAB.

4. Heart rate estimation performance criteria

The calculation of heart rate based on PPG signal (Figure 5) was performed by using low frequency filtering, signal derivative and peak searching. The HR estimate was filtered using moving average filter with a cut of frequency 0,11Hz.

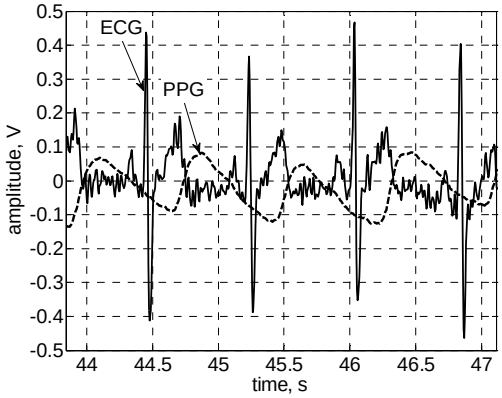

Figure 5. ECG and PPG signals while subject in rest

The subject motion causes the displacements of the sensor-to-tissue and tissue-to-bone interface (Figure 6) which in turn produces the PPG signal distortion (Figure 7).

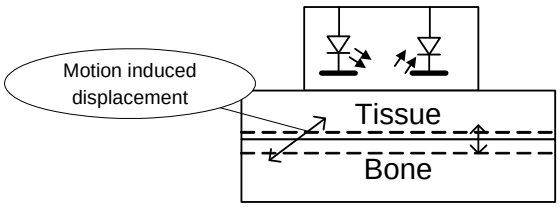

Figure 6. PPG signal registration

Subject motion influence on PPG signal is shown in Figure 7.

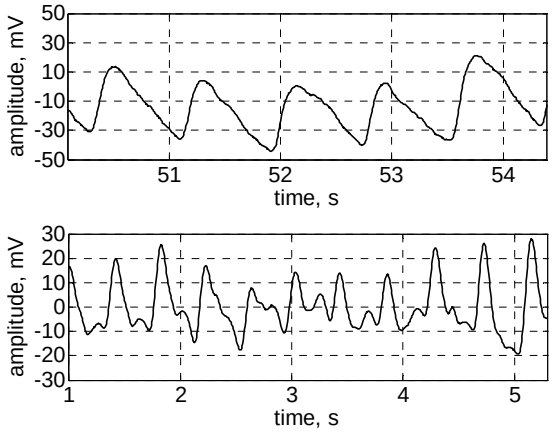

Figure 7. Subject motion influence on PPG signal. Top: PPG signal in rest; bottom: PPG signal in motion

Figure 7 indicates that the subject's motion causes significant PPG signal's distortion which subsequently leads to heart rate estimation errors.

Thus the ability to extract accurate physiological data from PPG sensor during subject activity remains a significant challenge [5]. Several attempts have been taken to search for the best PPG sensor placement on the body: it has been suggested to use a finger-wearable sensor in [6]; yet another study [7] investigated possibility to place the sensor on a wrist. Our research was undertaken in order to systematically investigate the aspects of PPG based estimation of heart rate in three different sensor positions on human body under different motion intensity.

Three performance indexes were used for the evaluation of heart rate estimated from PPG signals under different registration conditions:

a) correlation coefficient:

$$\rho = \frac{\sum_{n=1}^{N}\left[\left(r_{PPG}[n]-\bar{r}_{PPG}\right)\cdot\left(r_{ECG}[n]-\bar{r}_{ECG}\right)\right]}{\sqrt{\sum_{n=1}^{N}\left(r_{PPG}[n]-\bar{r}_{PPG}\right)^2}\sqrt{\sum_{n=1}^{N}\left(r_{ECG}[n]-\bar{r}_{ECG}\right)^2}} \quad (1),$$

b) mean of the difference $\Delta r = r_{PPG} - r_{ECG}$:

$$\overline{\Delta r} = \frac{1}{N}\cdot\sum_{n=1}^{N}\Delta r \qquad (2),$$

c) standard deviation of the Δr:

$$\sigma = \sqrt{\frac{1}{N}\cdot\sum_{n=1}^{N}\left[\Delta r - \overline{\Delta r}\right]^2} \quad (3).$$

5. Experiment results

Figure 8 shows an example of the set of raw signals registered during cyclical motion (PPG sensor on the forehead).

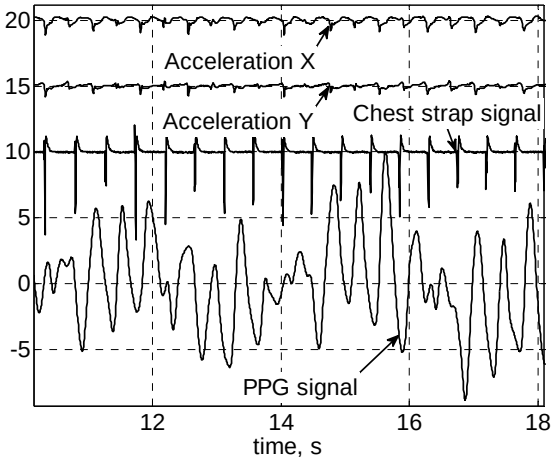

Figure 8. Registered signals

It can be observed that even at moderate motion intensity the PPG signal significantly differs from normal signal shown in Figure 5 and the heart rate is hardly discernable.

Figure 9 shows the correlation coefficient (obtained using the equation (1)) between the heart rate (HR) obtained from ECG and PPG sensors acquired in different physiological activity conditions. The placement of the sensor (positions are indicated in Figure 3) was varied and is indicated by three different curves.

It can be seen that forehead placement gives the best results even for complicated conditions. This observation can be explained by human anatomy: vision system which is placed in the head receives the least of motion. The wrist sensor, though being most technologically desirable, can be characterized as the worst performer.

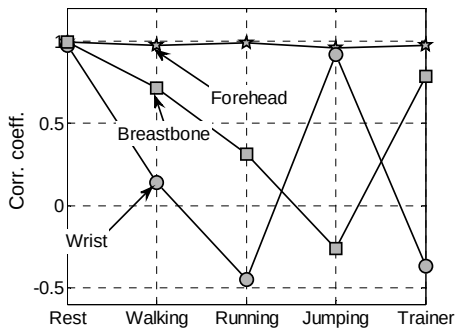

Figure 9. Correlation between ECG and PPG estimation for different sensor positions and motion intensity

The HR estimation accuracy based on ECG as a reference is presented as box-and-whisker plot in Figures 10-12. The box encloses 50% of the data (the interquartile range, IQR), a line in the box represents the median. Whiskers are 1.5 IQR. Dots represent the values out of this range.

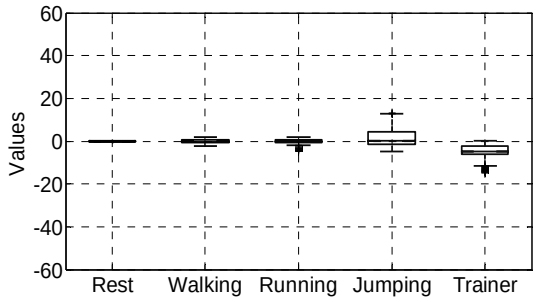

Figure 10. HR on forehead estimation

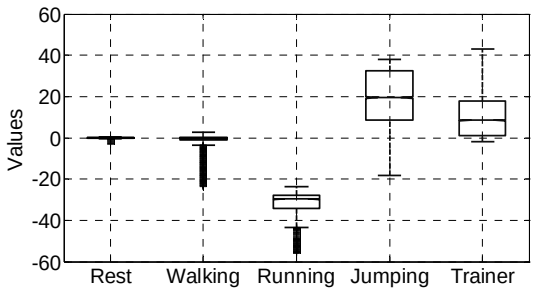

Figure 11. HR estimate on breastbone

The range of y axes in Figure 10 to Figure 12 was chosen the same in order to allow the results comparison.

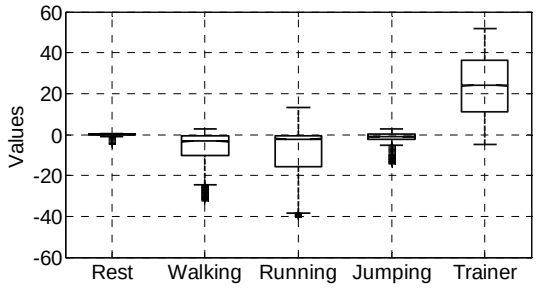

Figure 12. HR estimate on the wrist

Whisker diagrams again confirm that PPG sensor placement on forehead is the best position among all investigated.

The table 1 presents numerical results of sensor performance for forehead position. Even strong motion, e.g. jumping, does not increase the heart rate estimation error beyond limits as it was the case in other body places.

Table 1. Heart rate estimation performance using PPG signal when sensor was placed on the forehead

Movement condition	Corr. coeff.	Mean	Std
Rest	0.9964	-0.0069	0.1621
Walking	0.9723	-0.0904	0.8928
Running	0.9899	-0.2686	1.3289
Jumping	0.9562	1.5969	4.5568
Elliptical cross trainer	0.9735	-4.7784	3.4786

Investigation has been done in order to evaluate the ability to separate the errors sources. Signals from the wrist sensor were taken for the running subject case. Since it was assumed that there is no significant influence of motion axis on the clutter as explained in Figure 7, the accelerometer x and y axes (Figure 8) were combined taking their geometrical mean vector for calculation. Short Fourier transform was used on the acquired signals in order to evaluate the spectral content variation in time (Figure 13).

It can be seen that there is a great correlation in spectral content between the acceleration and the PPG sensor signal. Though it can be concluded that heart rate is changing smoothly, there is an intersection of the HR and motion induced frequencies. This is clearly seen on 30’th and 60’th second of the experiment.

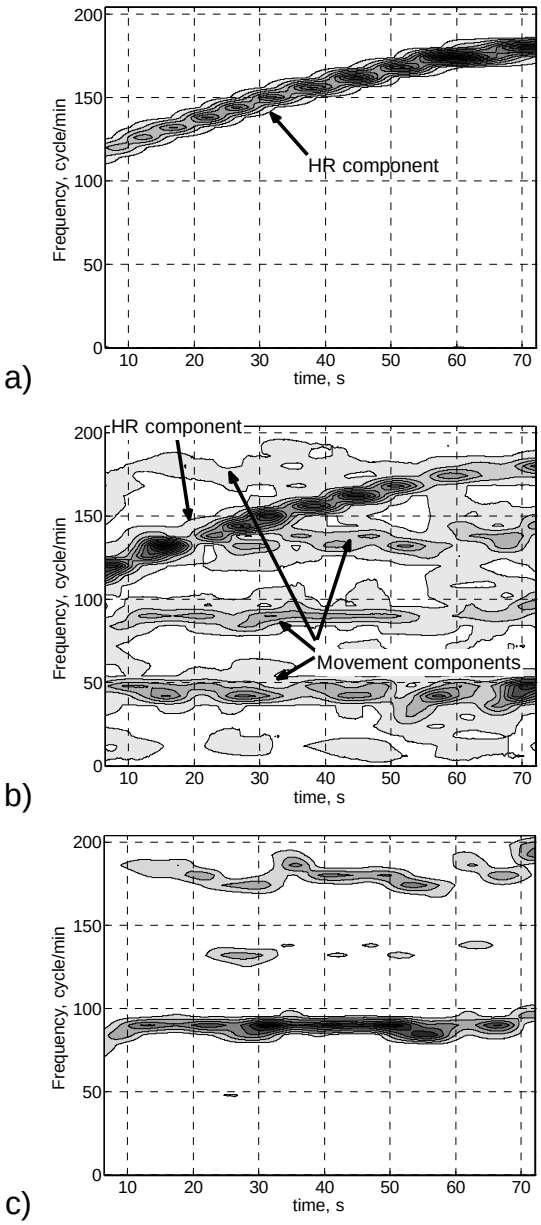

Figure 13. Temporal behavior of signals' spectrum for running subject: a) ECG, b) PPG, c) acceleration

6. Adaptive filtering

The last observation encouraged us to apply recursive least squares filter [8] for removal of motion induced noise from PPG signal. Figure 14 presents the structure of the filter and the flow of the signals.

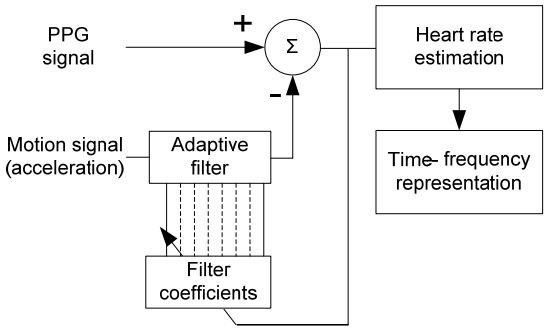

Figure 14. Adaptive filtering of PPG signal

There were the same signals used in this experiment as in Figure 13. The impact of adaptive filter to heart rate estimation results is illustrated in Figure 15.

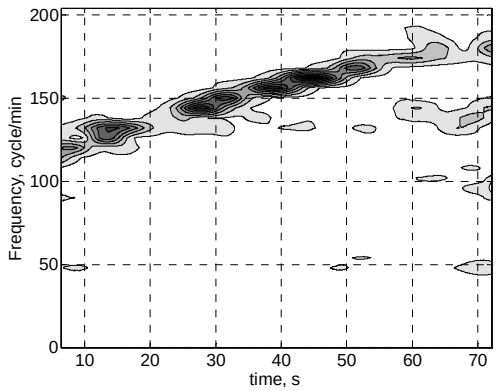

Figure 15. Illustration of PPG based time - frequency representation of heart rate when adaptive filtering to PPG signal was applied

Direct comparison of Figure 13b) and Figure 16 reveals that no 45Hz, 90Hz and 135Hz frequency components have been left after adaptive filtering; thus these components can be considered as the motion induced interference.

7. Conclusions

Analysis showed that spectrum of motion activity signal overlaps with the PPG signal. Heart rate computed from moving subject's PPG signal has significant high frequency component if we compare it with heart rate obtained using ECG chest strap. The most accurate results were obtained from the forehead PPG signal: lowest systematic error and the standard deviation of the random error were obtained. Experiments investigating the adaptive filter performance have been carried out. Preliminary results show favorable results: filter is

able to track the changing heart rate in the background of motion induced signals. Also other different schemes of adaptive signal processing may be applied. There good candidates would be the methods used in [9, 10].

References

[1] Hayes MJ, et al., "Quantitative Investigation of Artefact in Photo-plethysmography and Pulse-Oximetry for Respiratory Exercise Testing," Proc. of the CNVD 97 Frontiers in Computer-Aided Visualization of Vascular Functions, 1998, pp. 117-24.

[2] Sola A, Chow L, Rogido M, "Pulse Oximetry in Neonatal Care. A Comprehensive State of the Art Review," Anales of Pediatria, vol.62(3), 2005, pp. 266-80.

[3] Sami H.M., Kleinman B.S., and Lonchyna V.A. Central venous pulsations associated with a falsely low oxygen saturation measured by pulse oximetry // J Clin Monit, 1991. – Vol.7, - pp.309–312.

[4] Paunksnis A, Barzdziukas V, Jegelevicius D, et al. The use of information technologies for diagnosis in ophthalmology: Journal of telemedicine and telecare. Volume: 12 Pp: 37-40 Suppl. 1 2006.

[5] Yamaya Y., Bogaard H.J., Wagner P.D., Niizeki K., Hopkins S.R. Validity of pulse oximetry during maximal exercise in normoxia, hypoxia, and hyperoxia // Journal of Applied Physiology, 2002. – Vol.92, - pp.162–168.

[6] Asada H., Shaltis P., Reisner A., Rhee S., Hutchinson R. Mobile Monitoring with Wearable Photoplethysmographic Biosensors // IEEE Engineering in Medicine and Biology Magazine, 2003. – Vol. 22 (3), - pp.28-40.

[7] Renevey Ph., Vetter R., Celka P., Krauss J. Activity Classification Using HMM For Improvement Of Wrist Located Pulse Detection // BioSignal 2002, Brno, Czech Republic, June 26 - 28, 2002. – pp. 192-196.

[8] S. Haykin, Adaptive Filter Theory, NJ: Prentice Hall, Third edition, 1996, pp: 563 - 568.

[9] R.Kazys, L.Svilainis. Analysis of adaptive imaging algorithms for ultrasonic non-destructive testing. Ultrasonics 1995. Vol 33, No1. p.p.19-30.

[10] Marozas V, Janusauskas A, Lukosevicius A, et al. Multiscale detection of transient evoked otoacoustic emissions IEEE transactions on biomedical engineering Vol: 53 Issue: 8, Pp: 1586-1593: Aug. 2006.