Monitoring the Heart Rate in Cerebral Oximetry Signals

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Abstract

Cerebral oximetry of the frontal lobes based on Near InfraRed Spectroscopy (NIRS) is used to monitor brain tissue oxygen saturation in 2-4 s *intervals. However, higher sampling rates may enable heart rate (HR) monitoring. In total, 29 subjects were enrolled in 40* min *recording sessions. Cerebral oxy-haemoglobin (O_2Hb) concentration at 50* Hz *and the ECG were concurrently recorded. ECG was the reference for the HR algorithms based on the O_2Hb signal. The results show that accurate heart rate monitoring and beat detection on cerebral frontal lobe oximetry signals is feasible for normal heart conditions when the NIRS signals are sampled at high rates.*

1. Introduction

Monitoring oxygenation is critical in intensive care units or emergency departments, and several non-invasive techniques exist, although the most widespread one is the photoplethysmography (PPG) [1]. PPG to monitor tissue oxygen saturation is obtained via a pulse oximeter based on the transmission/reflection of light signals through/in a tissue under test. The oximeter is normally attached to the patient's index finger, but it can be worn in the ear, nose or toe [2]. Attached to peripheral parts of the body [3], pulse oximeters are unusable in emergency situations in which the cardiovascular system prioritizes vital organs (heart and brain) and hence, the blood flow reaching the extremities is very limited.

The search for a non-invasive cerebral oxygenation monitoring technique has become a challenge. One of the most promising alternatives is Near InfraRed Spectroscopy (NIRS). NIRS was demonstrated in 1977 by Frans F Jöbsis [4], and currently experiences a massive growth in medical scenarios such as cardiac surgery [5, 6], or as an emerging technology to monitor cardiac arrest patients [7]. NIRS rests on the transmission and absorption of NIR light as it passes through cerebral tissue. Light absorption analysis allows the calculation of concentration changes in oxy- (O_2Hb) and deoxy-haemoglobin (HHb), from which tissue oxygen saturation is estimated [6]. Currenlty, NIRS devices record cerebral saturation every 2-4 s.

Although the recording of saturation at those sampling rates is sufficient to monitor patient oxygenation, higher time resolutions may enable additional monitoring. Indeed, this study evaluates heart rate monitoring using a NIRS sensor of high time-resolution. Besides an accurate monitoring of the heart rate, a reliable detection of the heart beats using the NIRS signals would allow further analyses such as heart rate variability or the estimation of respiratory rate through respiratory sinus arrhytmia [2].

2. Materials and methods

2.1. Materials

Measurement system. Two independent systems were concurrently used to record the biomedical signals: (1) an experimental NIRS sensor (PortaLite, ArtiNirs) capable of recording haemoglobin concentrations at high sampling rates, and a BioPac system equipped with an ECG (ECG 100E), PPG (OXY 100E) and an impedance modules (NICO 100C) attached to a National Intruments data acquisition card (NI-6211, 16 bits/sample per channel). As shown in Figure 1, both systems were controlled

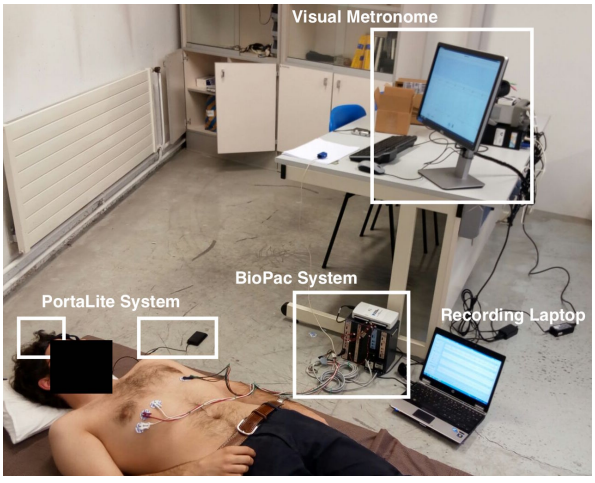

Figure 1. Photograph of a recording session showing the measurement system, electrodes and subject position.

via a single laptop. The recordings were synchronized using time-stamps on the resulting files. The ECG, impedance and PPG signals were sampled at 250 Hz and the cerebral haemoglobin concentration signals at 50 Hz (maximum allowed by the device). The ECG signal was used as gold standard to identify the heartbeats, and the O_2Hb concentration signal was used to identify beats and automatically compute the heart rate.

Measurement protocol. A protocol was designed to record 40-min of data per subject, subdivided into four 10-min sessions at different breathing conditions, including free-breathing and controlled breathing at slow ($9\,\mathrm{min}^{-1}$), normal ($12\,\mathrm{min}^{-1}$) and fast ($18\,\mathrm{min}^{-1}$) rates. Subjects lay in supine position within eye contact of a visual metronome to control the breathing rate, as shown in Figure 1. Lead II of the ECG was recorded, PPG at the left index finger, and the NIRS sensor was placed in the left hemisphere. Each recording session lasted about 1.5-2 h including breaks between sessions, subject preparation and quality checks of the recorded signals. Subjects were enrolled in the study after approval by the ethics committee of the UPV/EHU.

Final database. In total 29 subjects (20 female) were enrolled in the study. The median age, weight and height of the subjects was 24 years (23–28.5), 67 kg (58–72) and 168 cm (163-173.5), respectively. QRS complexes were automatically detected using the Physionet version of the `wqrs` detector [8], and were then manually revised and audited. The audited marks were stored in the database as gold standard for the beat detection and heart rate estimation algorithms based on the O_2Hb signal. For the present study only the ECG and O_2Hb concentration signals were used, Figure 2 shows an example of the signals used.

2.2. Methods

Two approaches were developed to monitor the heart rate (HR) using the O_2Hb signal. The first approach was based on a beat detection algorithm (peak detection), and the second exploited the quasi-periodicity of the signal in short intervals. As shown in Figure 2, in both cases the O_2Hb signal was first band-pass filtered to remove the DC offset and low frequency components (movement, respiration), and high frequency noise.

The beat detection algorithm followed a window approach. First the O_2Hb signal was forward-backward filtered using an order 8 elliptic bandpass filter (0.4–6 Hz and 1/40 dB equiripple). Then troughs of the signal were detected in 20-s intervals (windows) with an amplitude threshold of 10 % of the amplitudes of the troughs of the previous window and a refractory period between beats of 0.5 s. Additional troughs were searched for if consecutive trough separations exceeded 1.3 s (patch for false negatives). Then the process was repeated to detect peaks and a final check was made to ensure peaks and troughs were interleaved (patch for false positives and negatives).

Heart rates were computed using a 10 s sliding window with 50% overlap as the inverse of the mean RR-interval, $\overline{\mathrm{RR}}$, both for the audited beats and for those obtained from the O_2Hb signal, i.e.:

$$\mathrm{HR}\,(\mathrm{min}^{-1}) = \frac{60000}{\overline{\mathrm{RR}}\,(\mathrm{ms})}. \qquad (1)$$

The second approach to HR estimation exploited the quasi-periodicity of the preprocessed O_2Hb signal for short intervals. The method is based on the Average Magnitude Difference Function (AMDF) [9], which is extensively used in voice processing as a computationally efficient

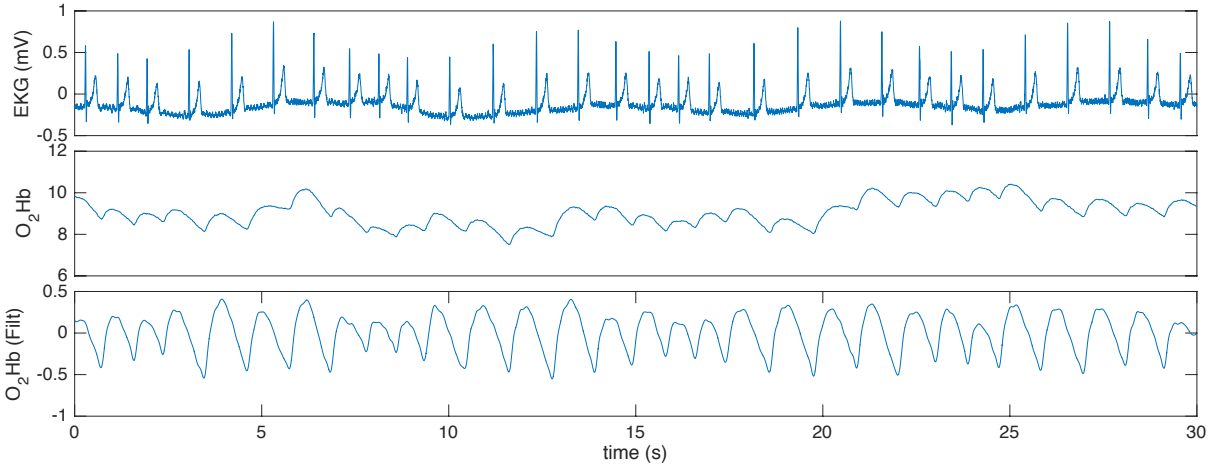

Figure 2. Example of the recorded signals showing heartbeats in the ECG and O_2Hb signals. Heartbeats in the O_2Hb are discernible after preprocessing (0.4-6 Hz), as shown in the bottom panel.

pitch detector. Indeed, the AMDF function for an L sample segment of the signal x is defined as:

$$D_x(n) = \frac{1}{L}\sum_{k=1}^{L} |x(k) - x(k-n)|,\ n = 1, .., n_{\max}, \quad (2)$$

and can be shown to be closely related to the autocorrelation function but avoiding the computationally demanding products [9]. In fact for a purely periodic signal the AMDF function presents local minima at the fundamental period and its multiples, as shown in Figure 3 for a 10-s segment of the O_2Hb signal. The fundamental period (mean RR interval) can be estimated as the second local minimum of $D_x(n)$, since $D_x(n)$ is minimum for $n = 0$, $D_x(0) = 0$. Heart rates were computed using a 10 s sliding window with 50% overlap. For every 10-s segment the AMDF was computed and T_0 was estimated as its second local minima. The HR was then estimated using T_0 (ms) instead of the mean RR interval in equation 1. Occasionally there was a large variation in RR intervals within the segment, caused mainly by the modulation of RR intervals by respiration. This compromises the periodicity of the O_2Hb signal and T_0 is not a good estimate for the HR. Those cases were identified by examining the regularity (intervals and depth) of the first 3 minima of the AMDF function (excluding $n = 0$). For irregular intervals the 10-s segment was subdivided into 4-s segments with 50 % overlap and the AMDF method was applied to each sub-segment. The HR was then estimated as the mean of the 4 values obtained in this way.

2.3. Evaluation

The heartbeats detected by the peak detection algorithm on the O_2Hb signal were compared to the audited annotations in the ECG (approximate delay 0.5 s), and true positives (TP), false positives (FP) and false negatives (FN) were identified. Then the Positive Predictive Value (PPV) and Sensitivity (SE) were computed for each recording session (respiration condition and patient).

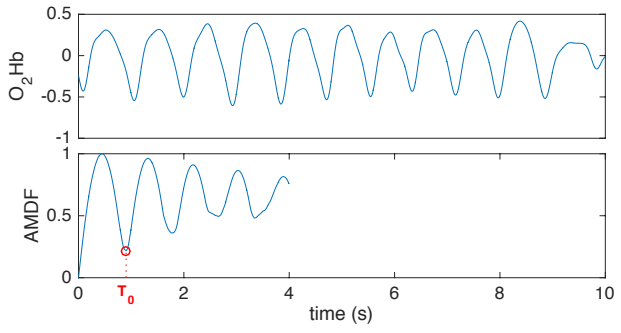

Figure 3. Estimation of the fundamental period (T_0) from the AMDF function, computed up to $n_{max} = 200$.

HRs obtained from the RR intervals of the audited ECG annotations were compared to those obtained from the peak detection algorithm and from the method based on the AMDF function. Bland-Altman plots and their corresponding limits for the 90% level of agreement were used to compare the HR values from the gold standard and the algorithms. In addition relative errors (ϵ_r), absolute relative errors ($|\epsilon_r|$) and concordance coefficients (ρ_c) were used to evaluate the precision of the HR monitors.

3. Results

The median HR and the inter-decile range (IDR) obtained using the audited annotations were 65.0 $\min^{-1}$ (55.5–78.9), for 10-s segments and 50 % overlap. The median coefficient of variation of the RR intervals in those segments was 0.06 (IDR, 0.02–0.13).

The peak detection algorithm was very accurate with an overall SE and PPV of 99.7% and 99.85%, respectively. Figure 4 shows the boxplots of the SE and PPV per patient for each respiration rate, which shows very good results with SE/PPV values above 98% in most cases.

Figure 5 shows the Bland-Altman analysis of the HR monitors. The HR monitor based on the peak detector is more accurate with LOAs of (-0.9–0.9), the LOAs for the method based on the AMDF function were (-2.8–1.4). Using peak detection, underestimation of the HR was caused by FNs while overestimation by FPs. The mean relative error and mean absolute relative error were 0.0 ($\pm$ 2.0) % and 0.5 ($\pm$ 2.0) % for the peak detector, and -0.6 ($\pm$ 3.7) % and 1.6 ($\pm$ 3.4) % for the AMDF method, and the concordance coefficients were 0.991 and 0.968, respectively. Errors and concordance coefficients for the different respiration rates are shown in Table 1, which shows that the precision did not vary significantly for the different respiration modes, and that the bias observed in the AMDF method occurred for all the respiration modes.

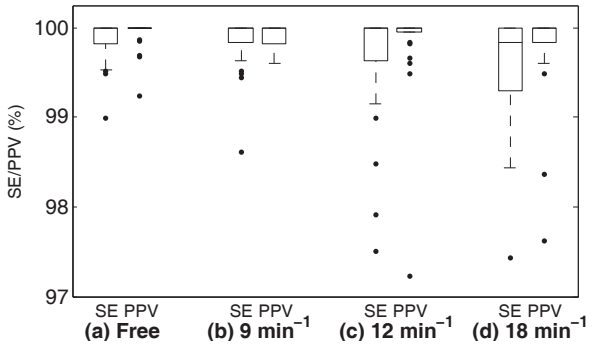

Figure 4. SE/PPV values of the beat detection algorithm grouped by respiration rates/modes.

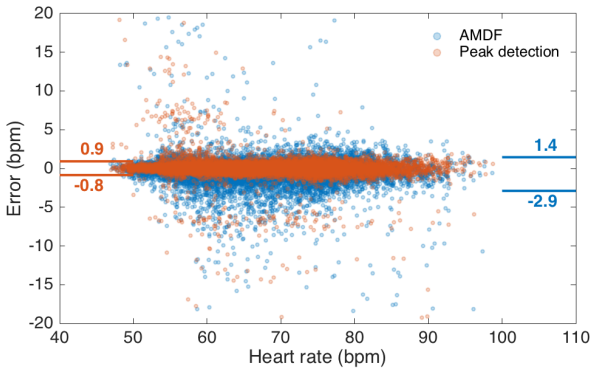

Figure 5. HR monitor errors compared with the GS.

Algorithm	$\epsilon_r(\%)$	$\lvert\epsilon_r\rvert(\%)$	ρ_c
Peak detector			
Free	0.01 (1.11)	0.29 (1.07)	.996
$9\,\mathrm{min}^{-1}$	0.13 (1.79)	0.47 (1.73)	.992
$12\,\mathrm{min}^{-1}$	−0.02 (2.24)	0.64 (2.14)	.986
$18\,\mathrm{min}^{-1}$	−0.07 (2.61)	0.61 (2.55)	.987
AMDF			
Free	−0.51 (2.38)	1.32 (2.04)	.984
$9\,\mathrm{min}^{-1}$	−0.37 (4.90)	1.80 (4.57)	.946
$12\,\mathrm{min}^{-1}$	−0.62 (3.83)	1.72 (3.48)	.960
$18\,\mathrm{min}^{-1}$	−0.74 (3.20)	1.47 (2.94)	.976

Table 1. Precision of the HR monitors for the different respiration rates, errors as mean (standard deviation).

4. Discussion

This study shows that an accurate heart beat detection is possible using the O_2Hb signal from a NIRS sensor, but this requires higher sampling rates than those customarily found in commercial cerebral oximeters. In addition two HR monitoring algorithms were demonstrated, and we found that the HR based on beat detection to be significantly more accurate than the HR based on the periodicity of the O_2Hb signal. The latter was negatively affected by variations in the RR intervals caused by respiratory sinus arrhythmia (subjects were young). An accurate beat detection in NIRS signals allows further analyses such as the estimation of the respiratory rate through respiratory sinus arrhythmia, or the computation of different heart rate variability indexes. Furthermore, cerebral oximetry is becoming increasingly important in the treatment of out-of-hospital cardiac arrest as an hemodynamic marker of the efficiency of cardiopulmonary resuscitation (CPR). In such scenarios, it is possible that higher sampling rates in NIRS sensors may result in more detailed information of the effect of CPR therapy.

Our results were obtained for healthy subjects in a controlled scenario, consequently the range of HRs were within normal limits. More challenging scenarios with either higher HRs or bradycardic patients may require slight modifications to the beat detection algorithm, such as adapting the refractory periods. In addition, in an out-of-hospital setting more elaborate preprocessing of the O_2Hb signal may be needed to avoid all sources of noise.

Acknowledgements

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