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Deriving respiration from high resolution 12-channel-ECG during cycling exercise

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Abstract: Monitoring of cardiac and respiratory activity, is essential in several clinical interventions like bicycle ergometries. The respiration signal can be derived from the ECG if it is not recorded itself (ECG derived respiration, EDR). In this study, we tried to reconstruct breathing rates (BR) from stress test high resolution 12-channel-ECGs in nine healthy subjects using higher order central moments. A mean absolute error per subjects of 2.9/min and relatively high correlation ($r_p = 0.85$) and concordance coefficient ($r_c = 0.79$) indicated a quite accurate reproduction of respiratory activity. The analysis of the different test stages revealed an increase of BR errors while subjects were effortful cycling compared to rest. During incremental cycling exercise test the mean absolute error per subjects was 3.4/min. Compared to the results reported in other studies at rest in supine position, this seems adequately accurate. In conclusion, our results indicate that EDR using higher order central moments is suited for monitoring BR during physical activity.

Keywords: central moments; EDR.

1 Introduction

In several clinical interventions, monitoring of vital parameters, cardiac and respiratory activity, is essential to control patients' safety. If the respiratory signal *per se* is not recorded, it can be extracted from the ECG (ECG derived respiration, EDR). Various approaches have been proposed in the past [1–3]. Recently, we introduced a new approach to quantify the decline of the ECG between R- and S-wave using higher order central moments [4]. Here, we applied this method to high resolution 12-channel-ECGs that were recorded during cycling exercise. Physical stress tests are common clinical diagnostic tools mainly for investigation of the cardiac status. The stress ECG is indispensable to unravel pathological changes of myocardial repolarization that are not visible at rest (e.g. in coronary artery disease or ischemic heart failure). Especially patients with cardiovascular impairments carry high risk of suffering from angina pectoris, ventricular arrhythmias and apnea during an exhausting exercise. But also in young healthy subjects the test might cause dyspnea or syncope. Therefore, it is essential to monitor health status of the participants to ensure an immediate termination of the test if indicated by vital signs. In general, heart rate and occurrence of arrhythmia are permanently controlled throughout the test. In this study, we try to estimate breathing rates from the ECG as second important parameter to be monitored.

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2 Methods

2.1 Cycling exercise test

Exercise testing was performed in upright position with an electronically braked cycle ergometer (Ergometrics 900, Ergoline, Bitz, Germany) with its seat and handlebar heights correctly set for each subject. After a resting period of 5 min and unloaded pedaling for 3 min, the incremental bicycle protocol started with the subject pedaling at 15 W. The power output was then increased by 15 W for every minute until the subject reached his or her limit of tolerance. Degree of effort was subjectively estimated by Borg scale rating (6–20) and objectively by achieved maximum lactate levels. Borg rating of perceived exertion >16 were regarded as indicators of sufficient effort. We encouraged all subjects to aim to maintain a pedaling frequency of 70–80 revolutions per minute throughout the test session. After a patient's individual limit of tolerance was reached, a cooling down phase ensued, consisting of 3 min pedaling at a slow rate (<40 revolutions/min) and a power output of 15 W. Afterwards, the participant remained seated for another 7 min without pedaling.

2.2 Data recording and preprocessing

High resolution 12-channel-ECG was acquired in nine young female healthy controls (age: 24.3 ± 3.4 years, BMI: 20.7 ± 1.7). Ten ECG leads, arranged in a standard scheme including six electrodes at the chest (V1–V6) and four at the extremities (left and right forearm and pelvis), were digitized at 4 kHz by CardioPart USB (AMEDTEC GmbH, Aue, Germany) and transformed to 12 channels (I, II, III, aVR, aVL, aVF, V1–V6). Input frequency range was 0–150 Hz for all leads. One channel with the least noise and artefacts was sampled down to 500 Hz and used for reconstruction of respiratory signals. ECG signal was bandpass filtered by a 45 Hz low-pass elliptic filter 3rd order and a 0.5 Hz high-pass elliptic filter 4^{th} order. After filtering the ECG signal the baseline wander was removed as proposed by De Chazal et al. [5]. Gas exchange measurements were carried out throughout the test (METALIZER 3B, Cortex, Leipzig, Germany). Respiration rates were automatically detected by the software and exported in mean values per time window lasting 30 s (MetaSoft, Cortex, Leipzig, Germany). Heart rate was estimated by extracting R-waves automatically from the ECG, visual inspection and averaging over time [6].

2.3 EDR based on central moments

The movement of the chest due to filling and emptying of the lungs leads to a displacement of the ECG electrodes resulting in an impedance change that effects RS-distances. Another reason for a morphological change of QRS-complexes is the stretching of the heart's apex towards the abdomen during inspiration. Additionally, the diaphragm is shifted downwards due to the filling lungs. During expiration the diaphragm is elevated in order to support emptying the lungs. Due to this effect, the apex of the heart is compressed towards the chest. The change of the apex's position causes a rotation of the electrical heart axis and therefore a morphological change of QRS-complexes dependent on the phase of respiration [7].

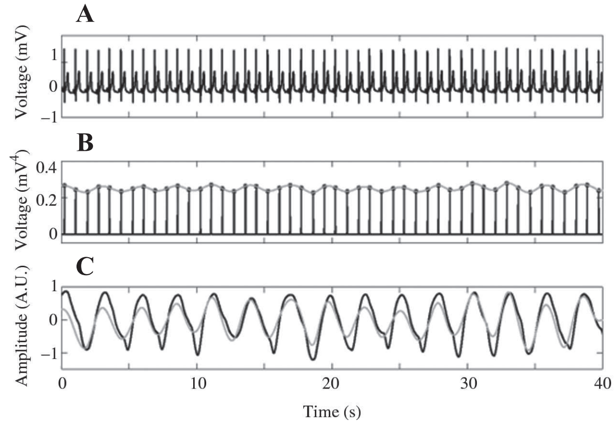

Figure 1: Example of ECG derived respiration (EDR) estimation by central moments. A: ECG, B: central moments of 4^{th} order in black with their maximum (black circles) interpolated by splines (gray curve), C: EDR curve (gray) and reference respiration signal (black).

In Schmidt et al. the quantification of RS-slopes by 4^{th} order central moments for EDR estimation was introduced [4]. This statistical measure is defined as:

$$m_4 = \frac{1}{L}\sum_{i=1}^{L}(x_i - \mu)^4. \tag{1}$$

The vector $X = [x_1, x_2, \ldots, x_N]$ is a segment of the ECG signal with the length L and μ is its mean value. 4^{th} order central moments were calculated in a sliding window of $L = 0.02s \cdot fs$ with a step width of $D = 1$. For the QRS-complex the corresponding 4^{th} order central moments show two peaks which represent the QR-slope and the RS-slope. For EDR-signal estimation RS-peaks were extracted. As illustrated in Figure 1A for every RS-interval the 4^{th} order central moment was calculated (Figure 1B, black lines). The maximum per heart beat was extracted. These anchor points (Figure 1B, black circles) were cubic interpolated and band-pass filtered between 0.05 and 1 Hz (Figure 1C, gray curve).

2.4 Comparison to reference respiration

For estimation of breathing rates inspiratory peaks were determined using an approach reported by Schäfer and Kratky [8]. This method is based on the evaluation of the vertical distance of inspiration and expiration extremes in the EDR-signal. A respiratory cycle was detected if the distance between respective maximum and minimum exceeded a threshold defined as the third quartile of the respiration signal weighted by a factor $x = 0.25$ [8]. Respiration rate in the current window was estimated by calculating the median of temporal differences of the maxima.

The breathing rate BR_{EDR} estimated on EDR was compared to the reference respiration frequency BR_{Ref}. Therefore, absolute E and relative absolute error e of the respiration rates was calculated in the i-th window.

$$E = \frac{1}{N}\sum_{i=1}^{N} |BR_{Ref}(i) - BR_{EDR}(i)| \quad (2)$$

$$e = \frac{1}{N}\sum_{i=1}^{N} \frac{|BR_{Ref}(i) - BR_{EDR}(i)|}{BR_{Ref}(i)} \cdot 100\% \quad (3)$$

2.5 Statistical analysis

For EDR rates' linear dependence on the reference rate we calculated Pearson correlation coefficient r_p, i.e. the quotient of covariance of X and Y (S_{XY}) and the standard deviations of X and Y (S_X, S_Y), with $X = f_{EDR}$, $Y = f_{Ref}$.

$$r_p = \frac{S_{XY}}{S_X S_Y} \quad (4)$$

In Lin et al. concordance coefficient r_c (eq. 4) was used to assess degree of reproducibility, that is not sufficiently covered by Pearson correlation coefficient [8, 9].

$$r_c = \frac{2S_{XY}}{S_X^2 + S_Y^2 + (\bar{y} + \bar{x})^2} \quad (5)$$

3 Results

Participants had a mean heart rate of 84.6 beats per min and breathed at 16 breaths per min at rest (see Table 1). Mean systolic to diastolic blood pressure was 120 to 81 mm Hg. Baseline lactate level of the group was 1.4 mmol/l. On average participants cycled until maximum load of 185 W was reached. Heart and breathing rate increased to a maximum of 182 and 44/min, respectively. Lactate level and subjective effort rating were 10 mmol/l and 19 on Borg scale.

In Figure 2 breathing rates derived from ECG and reference spirometry results of one participant are depicted in different states of the testing. The breathing rate of the subject increased considerably during exercise (stage III) to compensate for the rising effort of cycling. Respiration frequency peaked at the point of the highest load (at about 44/min). Reconstructed BR matched the reference value quite well. There were no obvious differences between the several stages of the exercise test.

Overall mean error of EDR rates was $E = 2.91 \pm 1.41$/min ($e = 13.47 \pm 7.66\%$). Mean Pearson correlation coefficient of EDR results and BR_{Ref} was $r_p = 0.85 \pm 0.09$ (all $p < 0.01$) with a concordance of $r_c = 0.79 \pm 0.12$. t-Test did not reveal a mean error different from zero. BR_{EDR} was not correlated to reference BR_{Ref} ($r_{Ref} = -0.01 \pm 0.16$, all $p > 0.05$). Thus, the accuracy of EDR was not dependent on actual BR.

In Table 2 errors of BR estimation by central moments at different stages of the recording are listed. During baseline the mean absolute error $E = 1.78 \pm 0.96$/min of BR estimates was lowest ($e = 10.50 \pm 5.25\%$). During unloaded pedaling errors increased moderately ($E = 2.91 \pm 1.66$/min, $e = 14.92 \pm 10.04\%$). While subjects started effortful cycling the accuracy of BR estimation decreased. The mean absolute error increased to 3.44 ± 2.13/min. Relative errors were only marginally changed from unloaded pedaling due to higher actual BR at exercise condition ($15.03 \pm 11.24\%$). During recovery errors of BR estimation were comparable to rest ($E = 1.96 \pm 1.17$/min, $e = 8.97 \pm 6.47\%$).

Table 1: Heart rate and breathing rate in different test states. Results at rest or maximum during recording are given in mean ± standard deviation.

Parameter	Mean ± standard deviation
$HR_{baseline}$ (1/min)	83.2 ± 13.4
$BR_{baseline}$ (1/min)	16.9 ± 4.1
$SBP_{baseline}$ (mm Hg)	120 ± 9.4
$DBP_{baseline}$ (mm Hg)	81.1 ± 7.4
$Lactate_{baseline}$ (mmol/l)	1.4 ± 0.6
HR_{max} (1/min)	182.3 ± 9.7
BR_{max} (1/min)	47.2 ± 6.5
P_{max} (W)	185.3 ± 34.6
$Lactate_{max}$ (mmol/l)	9.7 ± 1.9
$Borg_{max}$	18.9 ± 1.2

HR, heart rate; BR, breathing rate; SBP, systolic blood pressure; DBP, diastolic blood pressure; P_{max}: maximum load

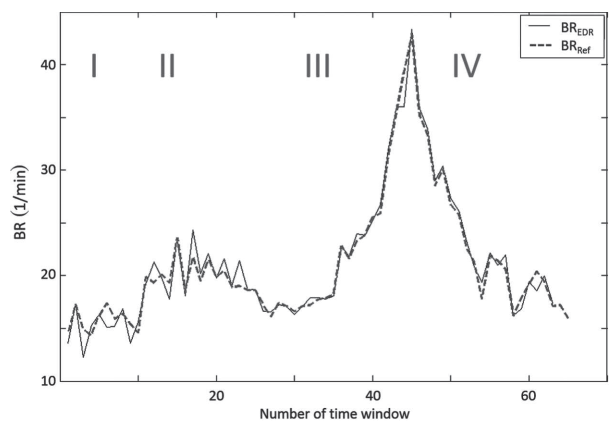

Figure 2: Reference (gray dashed line) and ECG derived (black solid line) breathing rate (BR) of one participant. Stage I: baseline, II: unloaded pedaling, III: cycling exercise, IV: recovery.

Table 2: Accuracy of breathing rate estimation by ECG derived respiration. Absolute error *E* [1/min] and relative error *e* [%] are given in mean ± standard deviation.

Stage	*E* [1/min]	*e* [%]
Beseline	1.78 ± 0.96	10.50 ± 5.25
Unloaded pedaling	2.91 ± 1.66	14.92 ± 10.04
Exercise	3.44 ± 2.13	15.03 ± 11.24
Recovery	1.96 ± 1.17	8.97 ± 6.47
All	2.91 ± 1.41	13.47 ± 7.66

4 Discussion

In this study we applied a new approach of deriving respiration from ECG recordings to stress test high resolution 12-channel-ECGs. Compared to spirometry results, the errors of breathing rate estimation were analyzed in the different stages of the test. The overall mean absolute error per subject was 2.91/min and was lowest at rest (1.78/min) and highest during exercise (3.44/min). A heart rate of 83/min demonstrate that participants are not as relaxed as during long resting state measurements in supine position. With a mean absolute error of 1.78/min at baseline the central moments approach appears quite precise. For example, Schäfer and Kratky achieved mean absolute errors of 1.14/min in supine position and cleaned 1 min analysis windows [8]. The fact, that accurary of BRs decline while subjects were pedaling seems to be logical, due to movement artefacts, arrhythmias and physiological noise contaminating the ECG. These distortions increase with exercise intensity during the test. Cardiorespiratory indices and levels of lactate and Borg scale indicated a very high individual effort to the limit of tolerance.

We found that EDR accuracy was strongly dependent on the correct detection of R-waves in the ECG. In segments with arrhythmias or artefacts preventing an adequate EDR reconstruction, produce outliers of estimated BRs. Therefore, we calculated the median BR in the analysis windows that is less susceptible to outliers. But in the future we want to test approaches for reconstructing the EDR signal also in distorted segments (e.g. by autoregressive modeling). In larger analysis windows the impact of outliers was even less, but our aim was to monitor breathing rate as vital sign during stress tests with sufficiently high temporal resolution.

One short-coming of our analysis is the automatic extraction of BR by the METALIZER software (MetaSoft, Cortex, Leipzig, Germany), that can not be adjusted in all detail. So differences of the detection of respiratory cycles may also contribute to the EDR errors in a systematic fashion. Additionally, a group consisting of nine young female volunteers is hardly large enough for statistical analysis and definitely not suited to draw generalized conclusions. Nevertheless, our results plead for the applicability of higher order central moments extracting BR from stress ECG recordings. Some methodological advantages of this approach are robustness against noise and drifts and no need for exact detection of characteristic peaks of the ECG except for R-waves. In conclusion, this was the first attempt to reconstruct respiratory activity from stress ECGs using using higher order central moments. Our results indicate that this EDR strategy is suited for monitoring BR with adequate accuracy and temporal resolution.

Author's Statement
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