Ventilatory Thresholds Estimation Based on ECG-derived Respiratory Rate

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Abstract

The purpose of this work is to study the feasibility of estimating the first and second ventilatory thresholds (VT1 and VT2, respectively) by using electrocardiogram (ECG)-derived respiratory rate during exercise testing. The ECGs of 25 healthy volunteers during cycle ergometer exercise test with increasing workload were analyzed. Time-varying respiratory rate was estimated from an ECG-derived respiration signal obtained from QRS slopes' range method. VT1 and VT2 were estimated as the points of maximum change in respiratory rate slope using polynomial spline smoothing. Reference VT1 and VT2 were determined from the ventilatory equivalents of O_2 and CO_2. Estimation errors (in watts) of -13.96 (54.84) W for VT1 and -8.06 (39.63) W for VT2 (median (interquartile range)) were obtained, suggesting that ventilatory thresholds can be estimated from solely the ECG signal.

1. Introduction

Determination of the aerobic threshold (AerT) and anaerobic threshold (AnaT) has remarkable practical importance. These physiological points can be used by coaches and athletes to control exercise intensity during training, design exercise programmes, measure training progress, and as predictors of performance and fatigue [1]. Furthermore, AerT and AnaT have also clinical applications, such as the prognosis of cardiorespiratory diseases. Different methodologies for estimation of AerT and AnaT during incremental exercise testing have been proposed in the literature. The "gold standard" in AnaT assessment is the analysis of blood lactate concentration [2]. It remains an invasive method that requires periodic blood sampling from subjects during an exercise maximal test, using specific equipment. Several non-invasive alternatives based on the analysis of respiratory gases have been proposed in the literature [3, 4]. Some researchers have previously reported the validity and reliability of exponential increases or respiratory rate breakpoints with respect to oxygen consumption as effective markers of ventilatory thresholds (VT) in trained athletes [4,5] and untrained sedentary individuals [6]. Techniques that involve respiratory exchange parameters enable the assessment of two VT during incremental load exercise: VT1 and VT2. These alternatives are highly reproducible and accurate, however, they require cumbersome devices that also interfere with natural breathing, as well as being very expensive and limited, accessible only in specialized laboratories and centres. For these reasons, studies based on electrocardiogram (ECG) derived parameters such as ventricular repolarization instability [7] or heart rate (HR) [1, 8] were developed by researchers as cheap, simple to perform and non-invasive methods for determining ventilatory thresholds. A computerised method that used polynomial spline smoothing presented in [9] has been employed to determine these abrupt accelerations in respiratory rate which are considered surrogates of VT1 and VT2. The objective of this work is to propose a new method that estimates VT using the respiratory rate derived from single lead ECG. This method, unlike those proposed in [4–6,9], does not require the analysis of oxygen consumption, so the use of a gas analyser is avoided.

2. Materials and methods

2.1. Database

Twenty-five males aged 33.4 ± 5.2 years volunteered to participate in this study. All of them were physically active, doing at least 3 days/week of regular aerobic training, and none of them had a diagnosed pathology/condition. The subjects were not active smokers. Each subject gave his written informed consent before participating in the investigation. The participants performed a submaximal cycle ergometer test (Quasar MED LT h/p Cosmos, Nussdorf-Traunstein Germany), divided in three stages: a 5-minute resting stage, during which the subjects remained sat and without talking, an exercise stage and a recovery stage. The exercise started at 75W on the cycle ergometer, increasing 25W each minute. The cadence frequency was fixed at 80 rpm, and the workload kept on increasing until the volunteers reached the 90% of their maximum HR (previously recorded from a maximal treadmill test performed in a different day), after that the load was kept for two more minutes. In the recovery stage they were asked to keep on pedalling at 75W for 3-5 additional minutes. The ECG was recorded using a high-resolution Holter (Mortara 48-hour H12+, Mortara Instrument, Milwaukee,Wisconsin) with a sampling rate of 1000 Hz. Leads I, II, III, aVL, aVR, aVF, V4, V5 and V6 were obtained. Recordings were performed at University of Zaragoza (Spain) and the study protocol was approved by the institutional ethics committee according to the ethical principles of the Declaration of Helsinki for Human Research. Study population characteristics are presented in Table 1.

Table 1. Study population characteristics (25 male volunteers). Values are presented as mean ± standard deviation, except from the maximum heart rate (Max. HR, provided as median [25th, 75th percentiles] since it was not normally distributed).

Age (years)	33.4 ± 5.2
Height (cm)	178.0 ± 5.5
Weight (kg)	74.8 ± 7.0
Body Mass Index (kg/m^2)	23.6 ± 2.1
Max. HR (bpm)	180.0 [172.0, 186.0]

2.2. EDR signal

An ECG-derived respiration (EDR) signal was obtained using the QRS slope range method [10], which exploits the respiratory-related variations of the QRS slopes. First, QRS-complexes were detected on lead V4 by using wavelet-based detector, applied on the ECG signal high-pass filtered with a cut-off frequency of 5 Hz, in order to attenuate T wave and minimize the number of bad detections. Identification of misdetections and ectopic beats was carried out, and instantaneous HR series was derived. Then the original ECG signal was bandpass filtered with 0.5 and 45 Hz cut off frequencies. QRS slope range was estimated from the first derivative of the ECG signal as the maximum slope minus the minimum slope within each QRS interval, starting 40 ms before R wave detection and ending 40 ms after. In some QRS morphologies it might happen that maximum slope is found before minimum slope in some beats and after it in others. To avoid this, the first 3 minutes of ECG are analyzed for each subject to determine if maximum slope appears predominantly before or after minimum slope, and this criterium is applied in the rest of the analysis restricting the search for the maximum slope to the interval before or after the minimun slope. Then, a median absolute deviation (MAD)-based outlier rejection similar to that used in [11] was applied to obtain the unevenly sampled EDR signal.

2.3. Respiratory rate measurement

An estimation of respiratory rate was obtained from the EDR signal by using a similar algorithm to that presented in [11]. This algorithm comprises 3 parts: the power spectrum estimation, the peak-conditioned average, and the respiratory rate estimation. Since the EDR signal was unevenly sampled and presented gaps due to outliers removal, Lomb's method was used for power spectrum estimation. Lomb's periodogram $S_k(f)$ is estimated in 40-s intervals (12-s windows with 50% overlap) every 5 sec [11]. Subsequently, in order to reduce the variance for the k^{th} interval, a peak-conditioned averaged spectrum $\bar{S}_k(f)$ is obtained considering only the five last spectra $S_k(f)$ that are peaked enough. Finally, $f_r(k)$ is estimated from $\bar{S}_k(f)$, only if it is peaked enough, based on the location of the largest peak. To ensure a reliable respiratory rate estimation, $f_r(k)$ must be higher than f_{min} Hz and it should be also located within a reference interval [$f_w(k) - \delta$, $f_w(k) + \delta$], where $f_w(k)$ is an exponential average of previous estimates. It is assumed that the respiratory rate may vary up to δ = 0.1625 Hz per 5s when the subject has already entered the exercise stage until before the end of this, and δ = 0.3 Hz in the transition from rest to exercise, because there is where the most significant changes in respiratory rate occur. The minimum estimated frequency is f_{min} = 0.125 Hz, since lower respiratory rates are not expected in exercise stress test. The value of forgetting factor in exponential average is β = 0.8, so as to $f_w(k)$ updates faster and follows the harshest changes. Subsequently, HR and $f_r(k)$ signals are interpolated with a 2 Hz sampling frequency prior to threshold estimation.

2.4. Ventilatory threshold estimation

An algorithm based on the one presented in [9] is used for estimating the ventilatory thresholds. The underlying hypothesis is that two separate abrupt accelerations in respiratory rate during incremental exercise, corresponding to VT1 and VT2, are observed. First, the exercise interval is selected from 80% to 90% of the maximum HR determined from a previous maximal treadmill test. In order to suppress small variations and maintain the expected trend of respiratory rate a sixth-degree polynomial spline was fitted to the interval. Then, the second-order derivative of the fitted line was calculated, obtaining another polynomial function which represents the acceleration and consists of 3 possible extremes: two maxima and one minima, or vice versa. The objective is to detect two local maxima that correspond to sharp increases in respiratory rate. If only one local maxima was present in the second-derivative the beginning or the end of the search interval is augmented taking into account whether the position of the peak was before or after the centre of the interval, respectively. If no local maxima was present the interval was augmented by both sides. The interval is augmented at the end by 5s, while at the beginning by 30s, due to the less available duration at the final part of the exercise stage. Finally, the first local maximum is taken as the estimation of VT1, and the second local maximum as the estimation of VT2. Ventilatory thresholds estimation on the selected exercise interval of the estimated respiratory rate for a representative subject are displayed in Figure 1.

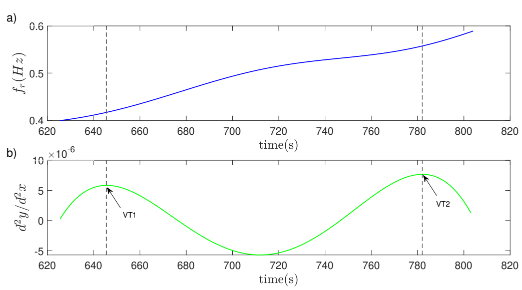

Figure 1. a) Interval of estimated respiratory rate during exercise testing in which the sixth-degree polynomial spline is fitted. b) Second-order derivate polynomial spline. Local maximum in this function implies respiratory rate accelerations that are taken as VT estimations.

2.5. Performance measurements

In order to evaluate the performance of the proposed method, the median and the interquartile range (IQR) of the error between the estimated VTs and a reference VTs determined by an expert in sport sciences is used. The reference VTs for each subject was obtained from the ventilatory equivalents of O_2 and CO_2, i.e., VE/VO_2 and VE/VCO_2, respectively.

For comparison purposes with previous studies, the results are presented in terms of workload. In this way, the estimations were converted from seconds to watts, assuming a linear increment of the workload. Estimation errors are also presented in terms of heart rate and oxygen consumption.

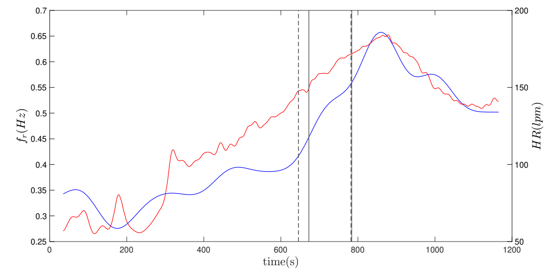

Figure 2. Temporal evolution of estimated respiratory rate (blue, left axis) and ECG-derived HR (red, right axis) during the exercise test for a given subject. The solid lines represent the time occurrences of reference VTs, whereas the dashed lines represent the time occurrences of estimated VTs.

3. Results

One subject had to be discarded due to missing reference VT and another one was excluded since respiratory rate could not be estimated from the ECG. Figure 2 shows an example of the respiratory rate and HR derived from the ECG signal of one subject, as well as the reference and estimated VTs. VT1 and VT2 could be identified in the remaining participants, with estimation errors shown in Table 2. In terms of workload, a median estimation error and IQR of -13.96 (54.84) W was archive in VT1 and -8.06 (39.63) W in VT2.

Table 2. VT estimation errors. Results are presented in terms of median of the absolute error followed by median the absolute relative error in brackets (%).

	workload (W (%))	HR (bpm (%))	V$_{\dot{o}_2}((L/min)(\%))$
VT1	-13.96 (8.89)	-2.16 (5.69)	-96.87 (9.10)
VT2	-8.06 (6.51)	-1.58 (2.97)	-12.94 (5.80)

Figure 3 shows a boxplot of the distribution estimation error ($\Delta\epsilon$(W)) of VT1 and VT2, calculated as the subtraction of estimated VTs minus reference VTs in terms of workload.

4. Discussion

This paper presents an alternative approach for identifying the ventilatory thresholds through increases in respiratory rate derived from the ECG signals. In most subjects ($\sim$ 80%) an error lower than 60 seconds was observed in VT2 estimation and lower than 120 seconds in VT1 estimation. Note that an error less than 60 seconds could represent an error of 0W in terms of workload, given that during the incremental cycling test the workload was increased 25W per minute. In a previous study [7], the per-

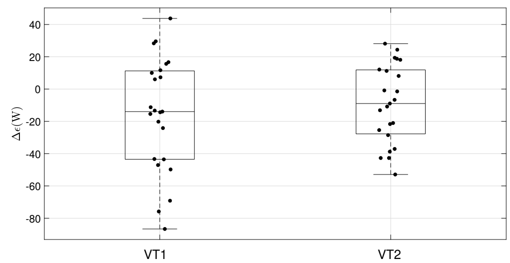

Figure 3. Boxplots of the error in the estimation of VTs. The filled circles represent the values for the different subjects.

formance of the ventricular repolarization instability (dT) and its low-frequency oscillations (LFdT) in estimating VT2 were studied, yielding dT slightly lower errors than in this work (-4.7 ± 25.2 W in terms of mean ± standard deviation), but require more than one lead to be employed, while the present methodology based on slope range technique can be implemented in single-lead ECGs. Results showed that abrupt increases in respiratory rate pattern are strongly associated with the ventilatory thresholds, being possible to take these points as effective markers for VT estimation. This work presents some limitations that must be highlighted. The first limitation is the small number of subjects ($n = 23$) who participated in this study. Moreover, they belong to a homogeneous group of healthy sportsmen in a relatively small age range. Therefore the range of ventilatory thresholds and maximum exercise values will be relatively small, and the applicability of the results in other populations should be investigated in further studies. Another limitation is the use of predefined HR thresholds obtained from a previous maximum effort test for identifying the accelerations in respiratory rate. However, same results were obtained when predicting the maximum HR from the age of the subject [12], overcoming this limitation. Note that the maximum HR is used only for setting the interval where the thresholds are searched.

5. Conclusions

The results suggest that VTs can be derived from accelerations in single lead ECG-derived respiratory rate. This non-invasive, simple and economic method could work well in this specific group of subjects for which it is applied, moreover it could be integrated in wearable devices like chest bands since it requires only one ECG-lead, resulting in appealing especially in outdoor sports.

Acknowledgments

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