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Transient and Steady State Estimation of Human Oxygen Uptake Based on Noninvasive Portable Sensor Measurements

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Abstract The main motivation of this study is to establish an ambulatory cardio-respiratory analysis system for the monitoring and evaluation of exercise and regular daily physical activity. We explored the estimation of oxygen uptake by using non-invasive portable sensors. These sensors are easy to use but may suffer from malfunctions under free living environments. A promising solution is to combine sensors with different measuring mechanisms to improve both reliability and accuracy of the estimation results. For this purpose, we selected a wireless heart rate sensor and a tri-axial accelerometer to form a complementary sensor platform. We analyzed the relationship between oxygen uptake measured by gas analysis and data collected from the simple portable sensors using a multivariable Hammerstein modeling method. It was observed that the resulting nonlinear multivariable model could not only achieve a better estimate compared with single input single output models, but also had greater potential to improve reliability.

Keywords Oxygen uptake; Portable sensors; Multivariable Hammerstein model; Nonlinear modeling; Support Vector Machine.

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1 Introduction

The main purpose of the paper is to explore the estimation of transient and steady state oxygen uptake using multiple noninvasive portable sensors. Oxygen uptake is an important physiological parameter for the determination of functional health status and clinical assessments in normal and pathological conditions. The potential application areas arising from this study thus include but are not limited to training monitoring for elite athletes, the rehabilitation of post coronary infarct patients, the health monitoring of patients with diabetes and heart diseases, and remote health assessment of elderly patients in telemedicine. Recently, practical portable sensors such as Triaxial Accelerometers (TA), pedometers, and heart rate (HR) sensors have been used for the estimation of fitness and of oxygen uptake during exercises [8] [1]. These sensors provide a potentially portable platform for the reliable estimation of oxygen uptake even under transitory and intermittent sensor failures or malfunctions which are often encountered for wireless portable sensors. An example of these sensor failures for a wireless HR sensor are artifacts generated by high impedance, body movements, and sudden disconnections. From a data fusion and fault tolerance point of view, the combination of sensors with different measuring mechanisms, which we call complementary sensor platforms, have many advantages [3]. By using complementary sensors we can also determine the fitness of exerciser as discussed in [15].

Based on this consideration, this paper selects the Polar wireless HR sensor and TA to estimate VO_2 (oxygen uptake). TA can evaluate the energy expenditure directly associated with body movement, and facilitate temporal tracking of the frequency, intensity, and duration of activity. On the other hand, HR is a measurement of the physiological response to exercise. These two kinds of sensors are therefore quite different in measurement mechanism. They have their own disadvantages as well. HR reflects the relative stress placed on the cardiopulmonary system due to activity [22], but it can also be elevated by emotional stress, which is independent of any change in oxygen uptake [8]. TA measures exercise intensity but cannot assess physiological responses. The combination of these two kinds of sensors can remedy these individual shortcomings. Furthermore, these sensors are cost effective portable sensors and easy to use. Based on the above consideration, we selected HR and TA to estimate VO_2 dynamically.

For the modeling of oxygen uptake, relevant papers in current literature have mainly concentrated on either steady state prediction [7] [9] or dynamic estimation of onset and offset of exercise [14] [23]. Paper [19] presented a novel SISO (single input single output) Hammerstein modeling (a static nonlinear block followed by a dynamic linear system) method to depict both steady state and transient of oxygen uptake. However, the estimation of oxygen uptake in paper [19] is based on the information of walking speed which is obtained from the motor speed of treadmill machine and is not applicable for free-living conditions. In this study, TA combined with a wireless HR sensor are used to dynamically estimate VO_2 as the replacement of the recording of walking speed. We also extend the SISO Hammerstein modeling method in [19] [20] to the multivariable case in order to cope with multiple sensor based estimation. Specifically, an exercise protocol based on PRBS (Pseudo Random Binary Sequence) dynamics was implemented to decouple the identification of linear dynamics from that of nonlinearities of Hammerstein systems. The support vector machine regression was applied to model the static nonlinearities. Multivariable ARX (Auto Regressive with eXternal inputs) modeling [12] approach was used for the identification of the dynamic part of the Hammerstein system.

Due to the total decoupling of the identification of the static part (based on steady state experiment data) and dynamic part (based on PRBS experiment data), by using the extended multivariable Hammerstein model identification approach, it is possible to apply different measurement equipments for steady state tests and dynamic experiments respectively. As a consequence, better estimation results are attainable [19].

In this paper, we only estimate VO_2 for moderate exercises (less than 100 w). We believe when the VO_2 estimation is in a relative wide range, the nonlinear modeling approach would be much more effective than the linear one. Some preliminary data from initial study on this topic was presented in the conference paper [18].

This paper is organized as follows. The extended multivariable Hammerstein model identification method and its associated experimental arrangements are introduced in Section 2. Modeling results and discussions are presented in Section 3. Section 4 gives conclusions.

2 Methodology

2.1 Subjects

Six untrained normal male subjects (aged 28 ± 5.5yr, height 176 ± 5cm, body weight 70 ± 11kg) participated in the experiments. All the subjects knew the protocol (approved by the Ethics Committee of the University of New South Wales) and the potential risks, and had given their informed consent.

2.2 Experimental equipments and data acquisition system

We need to accurately measure oxygen uptake, heart rate and body movement during treadmill exercise.

The measurement of **oxygen uptake** (either averaged or breath by breath) is implemented by using the AEI (Applied Electrochemistry Inc. USA) Moxus Metabolic Cart. Specifically, we use $S-3A/1$ Oxygen Analyzer to continuous measure oxygen concentration. The instrument has a sensitivity of 0.001% and time constant of $25-40$ milliseconds. Minute ventilation was measured during inspiration using a Turbine Flow Transducer$K520-C521$ (AEI). It can measure the flow range from 50 ml/sec to 16.5 L/sec. Before each individual exercise test, the turbine meter was calibrated using a 3.0 liters calibration syringe.

Heart rate was monitored beat by beat using a wireless Polar system. **Body movement** was monitored by using a triaxial accelerometer. The

Fig. 1 A typical experimental senario.

core part of TA was the ADXL210 (Analog Device, Inc.), a piezoresistive accelerometer supplied by Analog Electronics. The ADXL210 has a range of $\pm 10g$, a frequency range of 0-50 Hz.

The treadmill used in the system is the Powerjog "G" Series manufactured by Sport Engineering Limited, England. A computer control system was established for the treadmill. It can control the speed of the treadmill with a response time of less than 3 seconds, which is approximately twenty times faster than the increase in oxygen consumption that follows an increase in workload. This system can generate PRBS exercise protocol on treadmill. During experiments, all signals are synchronized with the PRBS signal.

2.3 Experimental procedure

A typical experimental scenario is shown in Fig.1. Initially, the subjects were asked to walk for about 10 minutes on the treadmill to familiarize themselves with the experiment. The subjects were then requested to walk at six levels of different speeds (2, 3, 4, 5, 6 and 7 km/h). Each level took a total period of 5 minutes, and was followed by a 10 minute resting period. The oxygen uptake was recorded and averaged every two minutes. In order to identify linear dynamic part of the Hammerstein system, subjects were also requested to walk on the treadmill under a PRBS exercise protocol. The breath by breath tidal volume and the concentration of oxygen were recorded to calculate breath by breath oxygen uptake. Throughout the experiments, the outputs of the TA and Polar HR sensor were also recorded.

2.4 Data pre-processing

The discussion about data pre-processing in this study mainly relates to wireless portable TA. The TA that were used are particularly suitable for detection of human movement due to their sensitivity to very low frequencies [4]. The TA was attached to the lower back close to the subject's centre of gravity. Accelerations were measured in a body-fixed axis system with measurement directions in antero-posterior (x), medio-lateral (y), and vertical (z). Individual outputs from the three measurements are high pass (0.11 Hz) and low-pass (20 Hz) filtered outputs to suppress the DC-response and other high frequencies that cannot be expected to arise from human movement. Filtered acceleration signals were calculated to produce accelerometer output variables I_{a_x},I_{a_y}, I_{a_z} and I_a [5]:

$$\begin{cases} I_{a_i} &= \frac{1}{T}\int_{t=0}^{T} |a_i| dt, \qquad i \in \{x, y, z\}, \\ I_a &= I_{a_x} + I_{a_y} + I_{a_z}, \end{cases} \tag{1}$$

where the integration interval T is selected as 5 seconds for the processing of dynamic experimental data (PRBS exercise protocol). For steady state experimental data, T is selected as 2 minutes (the last 2-minute interval at the end of each walking stage). As the outputs of TA, a_i ($i \in x, y, z$), are digitized (200 Hz), the integration in equation (1) is implemented simply using summation.

2.5 Multivariable modeling

2.5.1 SVR based nonlinearity identification method

In [2], Bai showed that the identification of linear part of a Hammerstein model can be decoupled from the nonlinear part with the help of the PRBS input. The reason is that any static nonlinearity can be exactly characterized by a linear function when the input has a binary nature, such as PRBS. Thus, the identification of Hammerstein model can be obtained by the identification of the static nonlinearity and the linear dynamic part separately.

For the identification of the nonlinearity, the so called ϵ-insensitivity Support Vector Regression (SVR) [21] is employed, which is convex and very efficient in terms of speed and complexity:

Let $\{u_i, y_i\}_{i=1}^{N}$ be a set of inputs and outputs data points ($u_i \in U \subseteq \mathcal{R}^d$, $y_i \in Y \subseteq \mathcal{R}$, N is the number of points). The goal of the support vector regression is to find a function $f(u)$ which has the following form

$$f(u) = w \cdot \phi(u) + b, \tag{2}$$

where $\phi(u)$ represents the high-dimensional feature spaces which are nonlinearly transformed from u. The coefficients w and b are estimated by minimizing the regularized risk function:

$$\frac{1}{2}\|w\|^2 + C\frac{1}{N}\sum_{i=1}^{N} L_\epsilon(y_i, f(u_i)). \tag{3}$$

The first term is called the regularized term. The second term is the empirical error measured by ϵ-insensitivity loss function:

$$L_\epsilon(y_i, f(u_i)) = \begin{cases} |y_i - f(u_i)| - \epsilon, & |y_i - f(u_i)| > \epsilon \\ 0, & |y_i - f(u_i)| \le \epsilon \end{cases} \tag{4}$$

This defines an ϵ tube. The radius ϵ of the tube and the regularization constant C are both determined by user. By solving the above constrained optimization problem, we have

$$f(u) = \sum_{i=1}^{N} \beta_i \phi(u_i) \cdot \phi(u) + b. \tag{5}$$

By the use of kernels, all necessary computations can be performed directly in the input space, without having to compute the map $\phi(u)$ explicitly. After introducing kernel function $k(u_i, u_j)$, the above equation can be rewritten as follows.

$$f(u) = \sum_{i=1}^{N} \beta_i k(u_i, u) + b. \tag{6}$$

Where the coefficients β_i corresponding to each (u_i, y_i). The *support vectors* are the input vectors u_j whose corresponding coefficients $\beta_j \neq 0$.

There are a number of kernel functions which have been found to provide good generalization capabilities, such as polynomials, radial basis function (RBF), sigmoid. The RBF kernel is given as follows:

$$k(u, u') = exp(-\frac{\|u - u'\|^2}{2\sigma^2}). \tag{7}$$

Additional details about SVR, such as the selection of radius ϵ of the tube, kernel function, and the regularization constant C, can be found in [13] [17] [21].

2.5.2 Multivariable ARX modeling

The general structure of a discrete time ARX model (with two inputs and one output) can be described as follows:

$$A(q)y(t) = B_1(q)u_1(t - n_{k_1}) + B_2(q)u_2(t - n_{k_2}) + e(t), \tag{8}$$

where $u_i(t)$, $y(t)$ and $e(t)$ are input, output and noise respectively, and

$$\begin{cases} A(q) & = 1 + a_1 q^{-1} + \cdots + a_{n_a} q^{-n_a}, \\ B_i(q) & = 1 + b_{i1} q^{-1} + \cdots + b_{n_{bi}} q^{-n_{bi}}, \;\; i \in \{1, 2\}. \end{cases} \tag{9}$$

If model order is determined the parameters of the model can be identified by using a least-square identification algorithm [12].

3 Results of multivariable modeling

3.1 Modeling of static nonlinearity

For the prediction of steady state oxygen uptake, book [9] proposed a famous linear static model to approximately estimate oxygen uptake in a given walking speed ranges. Paper [7] provided simple static nonlinear (polynomial) models. However, these models need walking speed information which is hard to measure accurately in free living conditions. In this study we establish not only a SISO model (HR vs VO_2, and TA vs VO_2), but also a multivariable model (HR&TA vs VO_2) based on SVR. The estimation results are shown in Fig.2 and 3. In Fig.2, the continuous curve stands for the estimated input output steady state relationship. The dotted lines indicate the ϵ-insensitivity tube. The plus markers are the points of input and output data. The circled plus markers are the support points. In Fig.3 a, the solid circle stands for the estimated value and solid arrow stands for the measured value.

In terms of curve fitting results (in the sense of root mean square (rms) error with unit $[ml \cdot min^{-1} \cdot Kg^{-1}]$), SVR regression is generally better than linear regression (LR). The best estimation is the multivariable model ($SVR_{rms} = 1.4$ and $LR_{rms} = 1.8$). TA based estimation ($SVR_{rms} = 1.7$ and $LR_{rms} = 1.8$) is less accurate than the multivariable model, but is much better than HR sensor based model ($SVR_{rms} = 2.7$ and $LR_{rms} = 3.0$).

We are not trying to prove that the multivariable model is better than SISO models or that TA based SISO models are better than HR based SISO models. To do so, more experiments would be needed to validate the identified models. However, the multivariable model does have advantages over the SISO model in that both TA and HR, which are both closely correlated to VO_2, can be used to identify abnormal states arising both from physiological factors as well as sensor malfunction. As discussed before, the HR sensor is a measurement of the physiological response to exercise while TA measure body movement. In normal conditions, the outputs of TA and HR should be closely correlated [16]. The data displayed in Fig. 4 was obtained under restricted conditions for healthy subjects. We applied ϵ-insensitivity SVR and identified the relationship between HR and TA. In Fig. 4, we marked the region of ϵ-tube as the normal zone, and the areas which are 3ϵ (as a threshold) away from regression curve as abnormal zone. The 3ϵ threshold selected in this paper, could also be replaced by other statistical parameters such as standard deviation or 95 % confidence limits. Note that under normal conditions almost all the data falls within the normal zone as shown in Fig. 4. Therefore, under normal conditions, using either a TA or HR SISO model can provide a good estimate of oxygen uptake. However, when an abnormal physiological condition unrelated to the exercise protocol occurs (for example arrhythmia or tachycardia) or a sensor malfunction happens, **the multisensor, multivariable approach has the potential to detect the abnormality and still provide a reasonable estimation.**

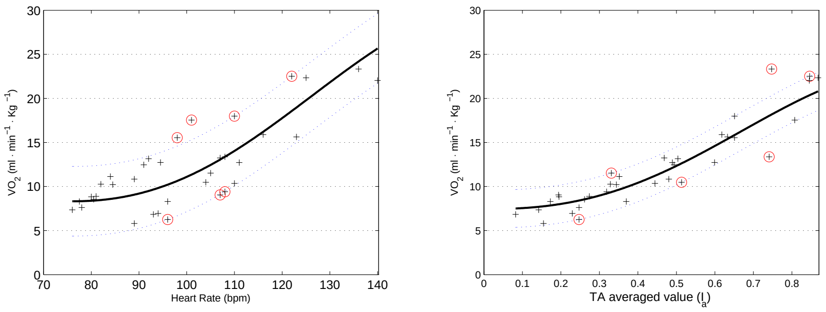

Fig. 2 SISO SVR regression: a) HR vs VO_2 (left). b) TA vs VO_2 (right).

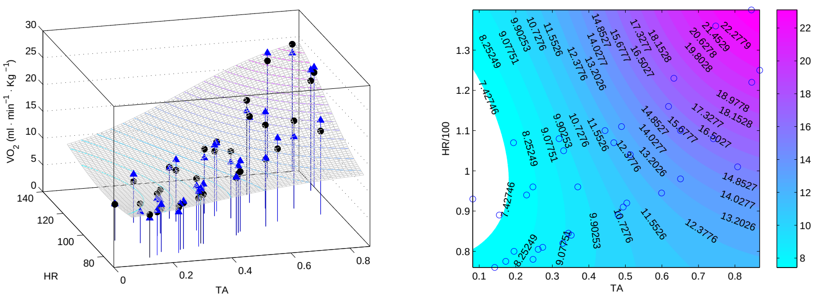

Fig. 3 Multivariable SVR regression for VO_2 estimation based on TA and HR signals: a) 3D plot (left). b) Contour plot (right).

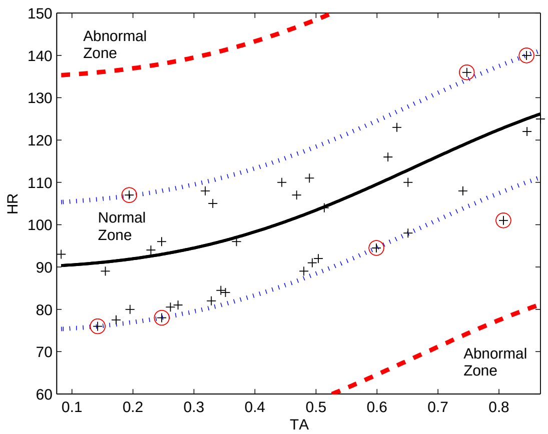

Fig. 4 Analysis of the relationship of TA and HR signals.

3.2 Modeling of dynamical part

In order to avoid coupling errors, a well designed PRBS exercise protocol is implemented in the automated treadmill system [19]. A PRBS has two levels ($a+$ and $a-$) and switches from one level to the other at constant time intervals Δ. The PRBS is periodic with a period $T = \Delta N$, where $N = 2n-1$ and n is an integer. In order to avoid nonlinear behavior, the difference of the two levels of PRBS should be as close as possible. However, it is also required that the output responses under these two levels of inputs should be noticeably different (good signal to noise ratio) to ensure a reasonable parameter estimation results. For the selection of Δ and N, we need to compromise with the complexity of the selected model, response time of the system, noise level, and the total experimental time which the subjects can tolerate. In this study, we select $a+ = 6km/h$, $a- = 4km/h$, $N = 7$ and $\Delta = 150$ seconds after several pre-experiments and detailed analysis of the modeling output.

Papers [6] [10] [11] often select first order exponential, with no time delays to describe the dynamics of oxygen uptake. In our previous study [19], we also confirmed that the exponential rise in oxygen uptake directly reflects the rate of rise and drop in leg muscle oxygen uptake at the onset and offset of exercises. Therefore, we select a first order ARX model (without delay) for the estimation of oxygen uptake. Based on the averaged data of **two** periods of 7 bit PRBS experiments, we identified the parameters of three individual models by using Matlab System Identification Toolbox. The prediction results are shown in Fig.5. In terms of the "fit" [12], the best fit for VO_2 transient estimation is the multivariable ARX model (77%). For the TA based model, $fit = 75\%$, which is much better than the HR based model ($fit = 53\%$). Fig.5 graphically shows that the multivariable model achieves the best transient predictions. **The heart rate response to exercise has a large time constant. In contrast the TA response to exercise is almost instantaneous. It is therefore not surprising that the dynamic model that incorporates both the TA and the HR response provides a much better fit and better matches the high frequency components. This is clearly demonstrated in Fig.5.**

4 Conclusion

In this study, we estimate oxygen uptake dynamically under free living conditions by using portable wireless sensors. We extended the Hammerstein model identification method proposed in our previous work [19] to the multivariable case. By using the data of a well designed PRBS type experiments, the identification of static nonlinear part and dynamic linear part is totally decoupled. The identified models can be applied in both steady state and dynamic analysis of human cardio-respiratory responses to exercises. Excellent fits and very low residual errors were obtained for the multivariable models incorporating both HR and TA data.

The results suggest that oxygen uptake during exercise can be estimated with an adequate degree of accuracy and sufficiently low complexity to be

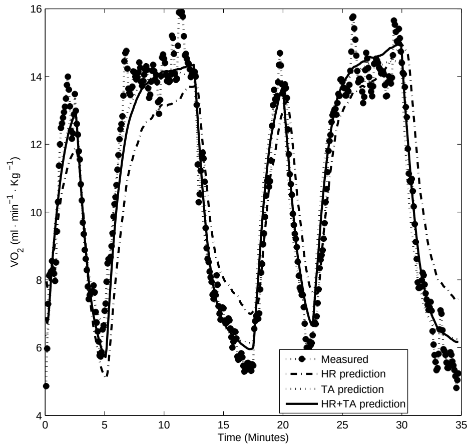

Fig. 5 Dynamic estimation of VO_2.

incorporated into wearable equipment. Such wearable monitors could be used to assess levels of health and fitness, improve training regimes for both the average person and high performance athletes, and to design training protocols that minimize exercise risk for patients undergoing post cardiac infarct rehabilitation.

Noninvasive portable wireless sensors can be prone to malfunctions and/or failures (such as, artifacts generated by environmental EMI and disconnection of electrodes). Another purpose of this study is to provide an efficient way to diagnose and compensate for sensor malfunctions and/or failures based on these identified models. Taking a multi-sensor, multivariable approach also reduces the impact of external factors on the overall estimation accuracy. Specifically, incorporating a triaxial accelerometer in addition to heart rate for estimating oxygen uptake from heart rate alone provides additional robustness to the estimation process, as heart rate is influenced by many parameters unrelated to external work. Furthermore, if multiple sensors are used, by checking the relationship of their outputs (e.g. Fig. 4), it is possible to detect physiologically abnormal functions. VO_2 estimation error can thus be significantly reduced by using an additional sensor not directly related to the physiological response (e.g. TA sensor).

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