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Estimation of Oxygen consumption during Cycling and Rowing

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***Abstract*—The aim of this paper is to develop estimator that can predict oxygen consumption (Vo_2) during cycling and rowing exercises, by using non-invasive and easily measurable quantities such as heart rate(HR), respiratory rate ($RespR$) and frequency of exercising activity. The frequency of exercise is quantified as a universal measure of exercise intensity and is known as Exercise Rate (ER). This ER is responsible for deviation in Vo_2 (ΔVo_2), HR (ΔHR), and $RespR$ ($\Delta RespR$) from their respective baseline measurements during exercise. Therefore, ΔVo_2 can be estimated from ΔHR, $\Delta RespR$ and ER. The resting measured of Vo_2 is referred as Vo_{2rest} ; this is computed from the physical fitness of an individual. The Hammerstein model is adopted for the estimation of ΔVo_2. Results in this study demonstrate that the developed estimators for each type of exercise are capable of estimating Vo_2 by adding up Vo_{2rest} and ΔVo_2 at various intensities during cycling and rowing.**

I. INTRODUCTION

Measurement of the oxygen consumption (Vo_2) has been regarded as an indicator of energetic demands during physical activities. It is measured as the most accurate physiological variable to quantify the intensity of aerobic activities. The recommendations of the *American College of Sports and Medicine* (ACSM) for exercise intensity use Vo_2 as the reference measure [1]. Direct measurement of Vo_2 during physical activities is unwieldy and, therefore, various methods have been developed and suggest for such estimation.

The literature [2-3] reveals that HR is an estimator of Vo_2 and various techniques have been developed to estimate Vo_2 based on HR. The traditional way for estimating the Vo_2 using HR is through recording of an individual's HR/Vo_2 calibration curve, separately tested in a laboratory. This estimation technique is based on steady state conditions and does not allow for the dynamic variation due to changing in exercise intensities in the $HR - Vo_2$ relationship. It is considered inaccurate to assume a constant level of Vo_2 when HR is low (e.g. the HR-flex method) [4]. The concluded remarks are that the effective prediction of the Vo_2 can only be achieved via individual calibration of HR, but only at a group level. The existing techniques inform only at a general view of physical activity but do not allow for precise estimation of Vo_2 transient response when human change their physical activity [3]. Other factors that have impact on HR responses include individual emotions, air temperature, body posture and many other non-metabolic factors. These non-metabolic factors distort the correlation between HR and Vo_2 [5-6]. To identify the metabolic and non-metabolic change in HR response, the respiratory rate is found as an important physiological parameter [7]. Firstbeat Technologies (Jyvaskyla, Finland) designed their estimator of Vo_2 using HR and $RespR$, adopting the neural network approach as a methodology [8]. Recently, this methodology is used to compare the estimation of $RespR$ and HR with their respective measurements during variety of physical activities. The evaluated performance of the proposed method is sufficiently accurate to determine the average Vo_2 in the field use. Again, it does not allow for the precise estimation of Vo_2 [9]. The advantage of this methodology is that no individual calibration is required. The relationship between exercise intensity and Vo_2, for example, in treadmill walking exercises, is modeled by using the Hammerstein approach [10]. The model gives the precise estimation of the transient and steady state behavior of the average Vo_2 for six subjects, hence limiting its effectiveness at group level. Thus this model is only useful for the control application.

The aim of this paper is to develop the estimators that can predict Vo_2 at different intensities during cycling and rowing exercises. The proposed estimators do not require any individual calibration for the subject to predict such a dynamic change in Vo_2 (ΔVo_2). The accurate prediction of ΔVo_2 allows for an accurate estimation of Vo_2 as the subject is engaged in exercise. The estimation of Vo_2 during exercise depends on the consumption of oxygen in resting (Vo_{2rest}) and change in oxygen consumption (ΔVo_2) from Vo_{2rest}. The most common methods in physiology for estimating Vo_{2rest} are the metabolic equivalent unit ($1\ MET$) [11-12] and the Harris Benedict equations [11,13]. During exercise ΔVo_2 is varied with intensity. The universal measure of intensity is introduced by our research group [14]. This measure is the frequency of the exercising activity, known as Exercise Rate (ER). This ER is responsible for producing the dynamic change in oxygen consumption (ΔVo_2), heart rate (ΔHR), and respiratory rate ($\Delta RespR$) during any typical aerobic activity. These measures ($i.e.\ ER$, ΔHR and $\Delta RespR$) are used for estimation of ΔVo_2 using Hammerstein model [15]. The block diagram of the proposed estimator is shown in Fig.1. Results in this study demonstrate that developed estimators for each type of exercise are capable for estimating Vo_2 by adding up Vo_{2rest} and ΔVo_2 at various intensities during cycling and rowing. The rest of the paper is organized as follows: Section II focuses on estimation method. Section III; describe the experimental equipment and exercising protocol and Section IV, targets the results and conclusion.

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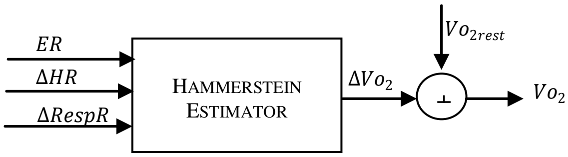

Figure.1 Block Diagram of Vo_2 Estimator

II. Estimation Method

Hammerstein- System

The Hammerstein model consists of two blocks, a static input nonlinearity followed by a linear dynamic system as shown in Fig.2.

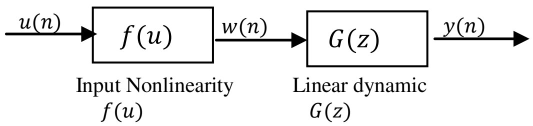

Figure.2 Hammerstein Model

The input static nonlinearity of the Hammerstein system is defined by the function $f(u)$ in Eq (1) transforming input $u(n)$ into nonlinear space. The dimensions of the input nonlinearity function are equivalent to the dimensions of the transpose of input vector $u(n)$. The dimensions of $w(n)$ and $u(n)$ are the same. The static nonlinearity $f(u)$ can be represented as sigmoid-net, piecewise linear, tree, and wave-net.

$$w(n) = f(u)u(n) \qquad (1)$$

$G(z)$ is the linear transfer function in Eq (2), It consists of two polynomial, $G(z) = Bii/Fjj$, where Bii is the polynomial that is dependent on the number inputs (nu). Fjj is dependent on number of the outputs (ny). $y(n)$ is the transformation of non-linear space $f(u)$ into linear space.

$$y(n) = G(z)w(n) \qquad (2)$$

The numerical optimization algorithm [16] is used to minimize the cost function that is given in Eq. (3). The goal of the optimization is to find the optimal parameters of the input static nonlinearity function in Eq. (1) and the optimal parameters of the linear system $G(z)$ by minimizing the error signal $(e(n))$ between measured output (y_{meas}) and estimated output (y_{est}).

$$V_N(G,f) = \sum_{t=1}^{N}(e(n))^2 \qquad (3)$$

III. Experimental Procedure

A) Subject

The estimation of static nonlinearity $f(u)$ and linear dynamic $G(z)$ of the Hammerstein systems are identified from the experimental data. The detail procedure of experiments is given in this section. In this study, three healthy male subjects are requested to perform cycling and rowing on a cycle ergo-meter and a rowing machine, respectively. Table-1 shows the physical characteristics of the subjects. Written informed consent was obtained from all subjects.

TABLE I

PHYSICAL CHARACTERISTICS CHART

	Age (years)	Height (cm)	Weight (Kg)	BMI	HRmax (bpm)
Subject 1	32	153	76	32.46	188
Subject 2	31	177	78	24.89	189
Subject 3	23	178	95	30.23	197

B) Experimental Equipments

To measure the ER during cycling and rowing exercises, a wireless triax accelerometer (TA) was deployed for detecting the accelerations of the body, a_x, a_y and a_z along x, y and z axes, respectively. These accelerations reflect the periodicity of the human body movement during rhythmic exercises. The TA was always mounted on the right thigh of the subject irrespective of the type of exercise. The time period of these accelerations are used to predict the exercise period (EP) along each axes, in real time. Among these three EP, the minimum EP is used to compute ER.

The respiratory belt is fixed firmly around the lower chest for measuring $RespR$ and it is connected with computer station (CS) using BNC connector via data acquisition system (DAQ62E).

The polar belt is used for measuring R-R interval. Data from the polar belt is received wirelessly. The receiver is connected with the CS, where R-R interval transformed into HR. At the next stage, HR data was down sampled to 1 sample/sec and filtered using a moving average filter with a 2 sec window. For system validity Vo_2 is measured using breath through a portable Cosmed KB4 analyzer (S.R.I, Italy); this was calibrated before and after exercise. The data was synchronized with the traix accelerometer.

C) Experimental Protocols

Each exercise was performed in separate sessions. The detail of exercise rates was reflected in table II. In each session, the subject was requested to take 5 minutes rest in a seated position. The mean value of Vo_2 during the resting period is considered as measurement of Vo_{2rest}. After the resting period the subject was requested to perform 10 minutes of each exercise with a recovery period of 10 minutes. Other datasets for each type exercise was achieved by giving the pseudo random binary sequence $(PRBS)$ signal at two different levels of frequency i.e. ER. Design of any nonlinear model was required for good starting values to converge to a global minimum [15]. In order to achieve this initial model, we implement the $PRBS$ signal for each type of exercise. A computer based system was implemented to generate the PRBS signal in the form of beeps at two different frequencies to reflect EP or a desired time period of the rhythmic movement. In case of cycling, it is 48 pedals/minute and 60 pedals/minute. For rowing exercise, it is 28 strokes/min and 30 strokes/min. A total of 15 datasets comprising 3 subjects during each type of exercise was obtained for this study. In these datasets, 4 sets of the data were obtained at four intensity levels (mentioned in Table II) and 1 set of the data for each subject was obtained from the PRBS signal. This means one subject performs the five sessions for one type of exercise.

TABLE II

EXPERIMENTAL EXERCISE INTENSITIES

	Intensity 1	Intensity 2	Intensity 3	Intensity 4
Cycling	36 pedals/min	48 pedals/min	60 pedals/min	72 pedals/min
Rowing	20 strokes/min	24 strokes/min	28 strokes/min	32 strokes/min

IV. ESTIMATION OF THE OXYGEN CONSUMPTION Vo_2

In this section, the problem of the estimation of Vo_2 is solved by using the proposed methodology. The solution to the problem is directed towards the division of the estimation algorithm into two steps. The estimation of Vo_{2rest} and ΔVo_2.

A) Estimation of Vo_{2rest}

The estimation of Vo_{2rest} can be done through several different equations. The suggested technique for estimating Vo_{2rest} is Harris-Benedict equations [13]. The oxygen consumption is expressed as ml/min for both men and women. It is correlated, as the dependent variable, with height, weight, age, and sex as the independent variables. The regression equation for men is given in Eq.4. In this equation ht is height and wt is weight. The measured and calculated value of Vo_{2rest} (Dividing by the respective weight of the subject) is tabulated in Table III.

$$Vo_{2rest} = 12.02 + 0.68(ht) + 1.93(wt) - 0.80(age) \quad (4)$$

TABLE III

MEASURED AND ESTIMATED VO_{2REST}

Subject 1		Subject 2		Subject3	
Vo_{2rest} (meas) ml/min/kg	Vo_{2rest} (est) ml/min/kg	Vo_{2rest} (meas) ml/min/kg	Vo_{2rest} (est) ml/min/kg	Vo_{2rest} (meas) ml/min/kg	Vo_{2rest} (est) ml/min/kg
3.78	3.21	2.78	3.1	3.13	3.137

B) Estimation of ΔVo_2

We develop the estimators of ΔVo_2 during cycling and rowing exercises by using the Hammerstein system. This nonlinear estimation method requires good starting values to quickly converge to a global minimum [17]. Initialization of the Hammerstein system during cycling and rowing exercises is carried out by estimating the arx model that is obtained from a PRBS signal. The model inputs are $ER, \Delta HR$ and $\Delta RespR$ and the model output is ΔVo_2. The model selections criteria, Minimum Description Length (MDL) and Akaike Information Criterion (AIC) are used for selection of the arx structure. It is interesting to note that both selection criteria suggest the similar arx structure for both types of exercises. The polynomials of the arx models for cycling and rowing exercises are given in table IV. This initial model is assigned in the Hammerstein system as initial guess. The input nonlinearity vector $f(u)$ is assigned as Sigmoid-net for ER, Piecewise linear for ΔHR and $RespR$. The order of nonlinearity for each input signal is selected based on the fitness of ΔVo_2. The maximum fitness is achieved by selecting the order (3,1,1) for each input nonlinearity. The nonlinear and linear dynamic block of the Hammerstein structure is estimated by using the matlab command 'PEM'.

TABLE IV

ESTIMATED ARX AND HAMMERSTEIN LINEAR BLOCK MODELS FROM EXPERIMENTAL DATA

ARX ESTIMATOR ESTIMATED FROM PRBS DATASETS DURING CYCLING $(y(t) = \frac{B}{A}u(t) + e(t))$	
$B_1(z) = 0.0835\ z^{-3}$ $B_2(z) = -0.0007164\ z^{-3}$ $B_3(z) = -0.01768\ z^{-3} + 0.01873\ z^{-4}$	$A(z) = 1 - 1.867\ z^{-1} + 0.8793\ z^{-2}$
ARX ESTIMATOR ESTIMATED FROM PRBS DATASETS DURING ROWING $(y(t) = \frac{B}{A}u(t) + e(t))$	
$B_1(z) = 0.412\ z^{-3}$ $B_2(q) = -0.002\ z^{-3}$ $B_3(q) = 0.0206\ z^{-3} - 0.02\ z^{-4}$	$A(z) = 1 - 1.67\ z^{-1} + 0.6813\ z^{-2}$
ESTIMATED LINEAR BLOCK $G(z)$ OF THE HAMMERSTEIN SYSTEM DURING CYCLING $(y(t) = \frac{B}{F}w(t) + e(t))$	
$B_1(z) = z^{-3}$ $B_2(z) = z^{-3}$ $B_3(z) = 0.006688\ z^{-3} + z^{-4}$	$F_1(z) = 1 - 0.8985\ z^{-1} - 0.7749\ z^{-2} + 0.6946\ z^{-3}$ $F_2(z) = 1 - 0.9005\ z^{-1} - 0.9814\ z^{-2} + 0.889\ z^{-3}$ $F_3(z) = 1 - 1.605\ z^{-1} + 0.7903\ z^{-2} - 0.3929\ z^{-3} + 0.2245\ z^{-4}$
ESTIMATED LINEAR BLOCK $G(z)$ OF THE HAMMERSTEIN SYSTEM DURING ROWING $(y(t) = \frac{B}{F}w(t) + e(t))$	
$B_1(z) = z^{-3}$ $B_2(z) = z^{-3}$ $B_3(z) = z^{-3} - 0.9652\ z^{-4}$	$F_1(z) = 1 - 0.221z^{-1} - 0.1974\ z^{-2} - 0.5079z^{-3}$ $F_2(z) = 1 - 2.72\ z^{-1} + 2.599z^{-2} - 0.8755\ z^{-3}$ $F_3(z) = 1 - 0.7866\ z^{-1} - 0.3626z^{-2} - 0.06152z^{-3} + 0.2238\ z^{-4}$

The PEM command uses the same cost function as describe in Eq. (3). The estimated input nonlinearity functions are shown in Fig. 2 and Fig. 3 for cycling and rowing, respectively. The Linear dynamic of the Hammerstein system is represented in the form of two polynomials against each input. The designed polynomials are given in Table IV for cycling and rowing exercises.

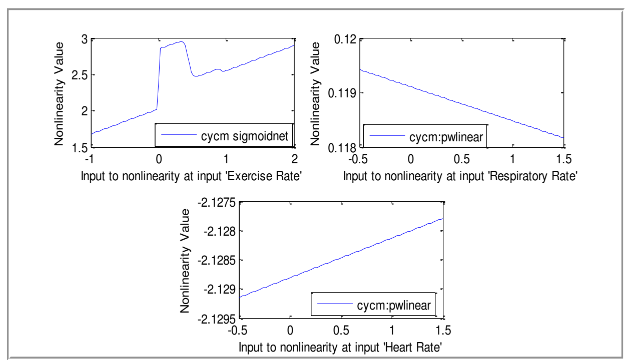

Fig. 2.The input nonlinearities of the Hammerstein Estimator with respect to ER, $\Delta RespR$ and ΔHR during cycling exercise

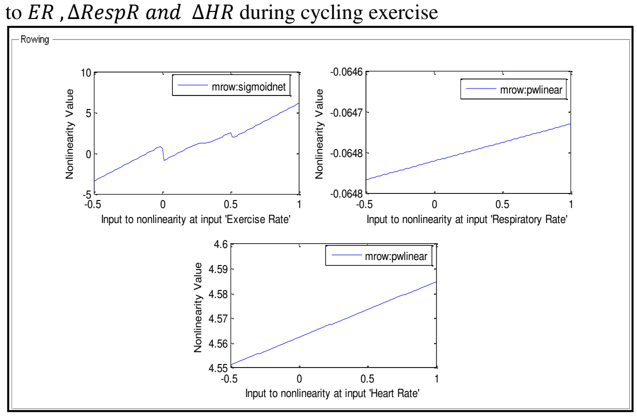

Fig. 3.The input nonlinearities of the Hammerstein Estimator with respect to ER, $\Delta RespR$ and ΔHR during rowing exercise.

TABLE V
PERFORMANCE COMPARISON

Hammerstein Estimator during Rowing Exercise						
Rowing Model	**Subject1**		**Subject2**		**Subject3**	
Strokes/ min	**MSE**	**FITNESS**	**MSE**	**FITNESS**	**MSE**	**FITNESS**
20	1.43	80.64%	1.2	78.25%	1.325	87.33%
24	1.21	89.04%	0.98	79.40%	1.25	90.19%
28	1.32	89.54%	1.05	81.80%	1.04	90.69%
32	1.21	91.14%	1.025	87.40%	1.02	93.45%
Hammerstein Estimator during Cycling Exercise						
pedals/ min	**MSE**	**FITNESS**	**MSE**	**FITNESS**	**MSE**	**FITNESS**
36	2.57	68%	1.35	71.95%	2.42	65.95%
48	1.62	77.37%	1.26	82.23%	1.70	80.64%
60	2.91	84.33%	2.91	87.44%	0.94	74.72%
72	1.22	90.54%	1.78	89.22%	2.21	80.65%

V. RESULTS AND CONCLUSION

The results and concluding remarks for this study is described in this section. The aim of this study as discussed earlier targets the design of estimators to estimate oxygen consumption without any need of individual calibration of the subject during cycling and rowing exercises. The performance of the design estimators are measured in terms of MSE in (ml/min/Kg) ^{2} and percentage of fitness against the measurement of ΔVo_2. This goodness of fitness is obtained by subtracting its normalized root mean square error (NRMSE). The performance of the proposed system using the new methodology for cycling and rowing is tabulated in table IV. Estimated ΔVo_2 and measured ΔVo_2 during cycling and rowing is given in Fig 4 and Fig 5. The results illustrate that the proposed Hammerstein estimator for each type of exercise is capable to estimate ΔVo_2 for various intensities of the respective exercise without the individual calibration. The Hammerstein estimator is not accountable for estimating ΔVo_2 with the change in exercising activity. The behavior of $f(u)$ for the Hammerstein system during cycling and rowing exercises is shown in Fig 2 and Fig 3 respectively, the input nonlinearity $f(u)$ for ER behave significantly in both types of exercises, while the behavior of non-linearity function for $\Delta RespR$ and ΔHR is almost same for both types of exercises. The developed estimator is useful for the design of the regulating system for Vo_2 without the need of actual measurement of Vo_2. In order to improve the safety and efficiency of an exercise prescription, future research should focus on the design of the regulator that regulates oxygen consumption without the need to focus on the actual measurement of Vo_2.

REFERENCES

[1] ACSM – American College of Sports Medicine. ACSM's "Guidelines for Exercise Testing and Prescription", Philadelphia: Lippincott Williams and Wilkins, 2001.

[2] Westerterp. K.R, "Assessment of physical activity: a critical appraisal". Eur J Appl Physiol, Vol 106, No. 6, pp. 823-828, 2009.

[3] inslie. P. N, Reilly. T, Westerterp. K. "Estimating human energy expenditure. A review of techniques with particular reference to doubly labelled water", sports Med, Vol 33, No 9, pp. 683–698, 2003.

[4] Ceesay. S. M, Prentice. A. M, Day. K.C, Murgatroyd.P.R, Goldberg G.R and Scott. W, "The use of heart rate kmonitoring in the estimation of energy expenditure : a validation study using indirect whole-body calorimetry", British Journal of Nutrition, Vol 61, pp. 175-186, 1989.

[5] Maas. S, Kok. M. L. J, Westra. H. G, Kemper. H. C. G. "The validity of the use of heart rate in estimating oxygen consumption in static and in combined static / dynamic exercise". Ergonomics, Vol 32, No. 2, pp. 141–148, 1989.

[6] Bot. S.D, Hollander. A. P, "The relationship between heart rate and oxygen uptake during non-steady state exercise", Vol 43, No. 10, Ergonomics, pp. 1578-1592, 2000.

[7] Pulkkinen. A, "The accuracy of new heart rate based methods to estimate oxygen consumption", M.S thesis, Uni of Jyvaskyla, Department of Biology of Physical Activity, 2003.

[8] Smolander. J, Juuti.T, Kinnunen. M. L, Laine. K, Louhevaara. V, Mannikko. K, and Rusko. H, "A new heart rate variability method for the estimation of oxygen consumption without individual laboratory calibration: application example on postal workers", Appl Ergon , Vol, 39: pp. 325–331, 2008.

[9] Smolander. J, Ajoviita. M, Juuti. T, Nummela. A and Rusko. H. "Estimating oxygen consumption from heart rate and heart rate variability without individual calibration". Clin Physiol Funct Imaging, Vol. 31, pp. 266-271, 2011.

[10] Su. S. W, Wang. L, Celler. B. G and Savkin. A.V, "Oxygen Uptake Estimation in Humans During Exercise Using a Hammerstein Model", Annals of Bio Med Engineering, Vol. 35, No. 11, pp. 1898–1906, 2007.

[11] Pettitt. R. W, Pettitt. C. D, Cabrera. C. A and Murray. R. S. "A Theoretical Method of Using Heart Rate to Estimate Energy Expenditure During Exercise", International Journal of Sports Science & Coaching, Vol 2, No. 3, 2007.

[12] Brooks. G. A, Fahey. T. D. and Baldwin. K. M, "*Exercise Physiology*", 4th ed: Mayfield Publishing, Mountain View, 2005.

[13] Pellet. P. L, "Food Energy Requirements in Humans", American Journal of Clinical Nutrition, Vol 41, pp. 711-722, 1990.

[14] Cheng. T. M, Savkin. A. V, Celler. B. G, Su. S.W, and Wang. N, " A universal algorithm for exercise rate estimation in waking, cycling and rowing using triaxial accelerometery, Electronics Letters, Vol 45, No.8, pp. 394-395, 2009.

[15] Bai. E. W. "An optimal two-stage identification algorithm for Hammerstein–Wiener nonlinear systems", Automatica, Vol 34, No. 3, pp. 333–338, 1998.

[16] Jorge. N, and Stephen. J. W: "Numerical Optimization", Springer, Series in Operations Research, 1999.

[17] Bai. E. W, "A blind approach to the Hammerstein model identification", IEEE Trans, Signal Proce, Vol 50, No. 7, pp.1610–1619, 2002.

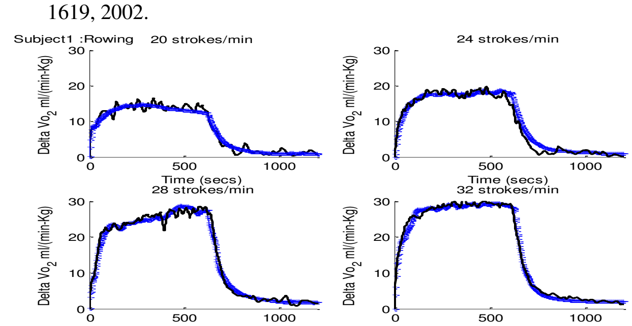

Figure. 4 Estimated ΔVo_2 and measured ΔVo_2 during rowing.

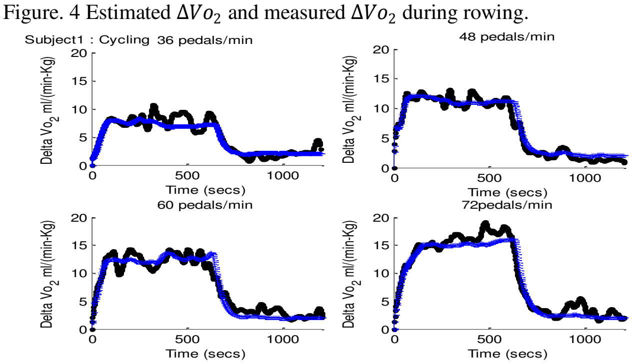

Figure. 5. Estimated ΔVo_2 and measured ΔVo_2 during cycling.