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Nonparametric Model Prediction for Intelligent Regulation of Human Cardiorespiratory System to Prescribed Exercise Medicine

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ABSTRACT Intelligent regulation for human exercise behaviors becomes significantly necessary for exercise medicine after the COVID-19 epidemic. The key issue of exercise regulation and its potential development for intelligent exercise is to describe human exercise physiological behaviors in a more accurate and sufficient manner. Here, a non-parametric modeling method with kernel-based regularization is presented to estimate cardiorespiratory biomarkers (i.e., oxygen uptake ($\dot{V}O_2$) and carbon dioxide output ($\dot{V}CO_2$) by merely non-invasively monitoring the indicator of exercise intensity (e.g., walking speed). Using the kernel-based non-parametric modeling, we show that $\dot{V}O_2$ and $\dot{V}CO_2$ behaviors in response to continuous and diversified exercise intensity stimulations can be quantitatively described. Furthermore, the dataset from the stairs experiment with a proper protocol is applied in the kernel parameter selection, and this selection approach is compared with the numerical simulation approach. The comparison results illustrate an improvement of 4.18% for oxygen uptake and 7.63% for carbon dioxide output in a half period, and 11.00% for oxygen uptake and 12.60% for carbon dioxide output in one period when using the kernel parameter selected from the stairs exercise. Moreover, the advantages of using the non-parametric model, the necessity of sufficient stimulation for identification and the importance of the kernel regularization term are also addressed in this paper. This method provides fundamental work for the practice of intelligent exercise.

INDEX TERMS Exercise medicine, intelligent exercise, non-parametric modeling, oxygen uptake, carbon dioxide output.

I. INTRODUCTION

Since exercise medicine by American College of Sports Medicine (ACSM) in 2007 that exercise is standardized as a part of a disease prevention and treatment medical paradigm, the exercise prescription has been acceptable in the clinical medicine [1]. The COVID-19 pandemic is currently causing another health risk - physical inactivity [2].

Exercise prescription is based on the exercise intensity that is often detected by Oxygen Uptake ($\dot{V}O_2$) and Heart Rate (HR) [3], [4]. In aerobic exercise activities, exercise speed combined with durative time is introduced to identify the exercise intensity [5], [6]. Motor controlled exercise fitness equipment (e.g., treadmill and cycle ergometer) are usually

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used to prescribe and standardize the exercise intensity. The stimulation type of exercise intensity often includes continuous and intermittent exercises determined by uniform and various exercise intensities in the exercise workout respectively. The current practice on clinical medicine mainly is based on the open-loop or pseudo-close-loop regulation, while human exercise physiological responses cannot be predictably bounded in association with certainly stimulated exercise intensities. Thus, the modelling work of cardiorespiratory responses to exercise is critically necessary for the development of exercise intelligence in prescribed exercise medicine.

The term "oxygen debt" is the first physiological interpretation for human exercise and recovery by A.V. Hill [7]. The body's carbohydrate stores are linked to energy "credits". If these stored credits are expended during the exercise workout, then a "debt" occurrs. The greater energy "deficit", or use of available stored energy credits, the larger energy "debt" occurs. In 2014, the equivalent physical model of the "oxygen debt" hypothesis is found based on the structure of a switching resistance-capacitor circuit [8]. In the last decades, the model identification methods such as fixed-order linear time-invariant models are used for the model-based control of cardiorespiratory behaviors. Based on the parametric modelling only limited physiological information is acquired. Thus, the exercise scene with the known exercise intensity can be theoretically acceptable such as computer-controlled treadmill exercise.

However, the parametric model prediction paradigm may fail in the outdoor exercise prescription because of dynamical variability and uncertainty of the exercise intensity lead to a decline in modelling accuracy and robustness. Furthermore, advanced sports formulations (e.g., interval training) have been confirmed as an effective way to improve cardiorespiratory fitness and prolong healthy lifetimes. In this sense, adequate aerobic activities (e.g., swimming, stair-climb, running, cycling, etc.) with intelligent guidance are sufficient to accommodate the complex exercise physiological behaviors in the real world.

Here, we present a nonparametric model prediction that is not based on the complexity selection of model identification, more importantly, is neither based on model structure nor model parameter optimization, but based on the states of massive input information. The nonparametric model prediction essentially involves two assumptions: (1) human cardiorespiratory responses to exercise can be quantified with complex interactions between exercise intensity and HR/$\dot{V}O_2$/$\dot{V}CO_2$ responses. Any exercise includes sufficient and diversified stimulations which always simultaneously and frequently influence the physiological network. And (2) the dynamic characteristics of the cardiorespiratory response originating from the source are vulnerable to disturbance and uncertainty. Instead of identification by fixed-order linear time-invariant systems, we define a kernel with regularization terms on the basis of the nonparametric modelling. To achieve this, we use exercise intensity as the input, $\dot{V}O_2$ or $\dot{V}CO_2$ as the output. The input-output interaction is described by Impulse Response (IR) and its numerical realization is estimated by the stable spline kernel-based regulation. The kernel-based non-parametric method is mainly applied in identifying how the $\dot{V}O_2$ or $\dot{V}CO_2$ response to treadmill speed. Two approaches are compared in the selection of the kernel parameter in this methodology. One approach is the numerical simulation which has been proposed in our previous paper [9], and the other approach is selecting the parameter of the kernel in the regularization term based on identification results when using data from the stairs experiment.

II. METHODS

In this section, we illustrate the non-parametric modeling method that is applied for the $\dot{V}O_2$ and $\dot{V}CO_2$ identification during the treadmill exercise. The experiment is introduced afterward, which contains the stairs experiment and treadmill experiment. Two different selection methods for the parameter of kernel including the numerical simulation and tuning from stairs experiment are also introduced for the non-parametric modeling of treadmill exercise.

A. NON-PARAMETRIC MODELING OF FINITE IMPULSE RESPONSE BASED ON KERNEL

The non-parametric modeling method based on kernel is conducted to discern how the $\dot{V}O_2$ or $\dot{V}CO_2$ reacts to treadmill speed. Under the discrete case, the relationship between treadmill speed (input) and $\dot{V}O_2$ or $\dot{V}CO_2$ (output) can be considered as a single input single output (SISO) system which can be calculated by impulse response (IR) as Eq. (1):

$$y(t) = \sum_{\tau=0}^{\infty} u(t-\tau)g[\tau] + \varepsilon(t), \quad t = 1, 2, \ldots, N, \tag{1}$$

where $u(t)$ is the input (exercise phase), $y(t)$ is the output ($\dot{V}O_2$ or $\dot{V}CO_2$), $g(\tau)$ represents the parameter of IR, t is the sampling time, $\varepsilon(t)$ is Gaussian white noise, and N is the total number of sampling.

The $\boldsymbol{\theta} \in \mathbb{R}^m$ is defined which contains the Finite Impulse Response (FIR) coefficients [10]:

$$\boldsymbol{\theta} = [g_1, g_2, \ldots, g_m]^T. \tag{2}$$

Based on the regression vector φ and $\boldsymbol{\theta}$, the FIR model could be described as [11]:

$$y(t) = \varphi^T(t)\boldsymbol{\theta} + \varepsilon(t), \quad \boldsymbol{\theta} \in \mathbb{R}^m \tag{3}$$

The Eq. (3) could be rewritten in vector form by stacking all the elements (rows) in $y(t)$, $\varphi^T(t)$ and $\varepsilon(t)$ to form the vectors $\boldsymbol{Y}$, $\boldsymbol{\phi}$ and $\boldsymbol{\varepsilon}$ and obtain:

$$\boldsymbol{Y} = \boldsymbol{\phi}\boldsymbol{\theta} + \boldsymbol{\varepsilon}. \tag{4}$$

Then the minimum value of the cost function in terms of estimation error can be solved by least square estimation. Thus the estimated parameter $\boldsymbol{\theta}$ is written as [10]:

$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}\in\mathbb{R}^m} \|\boldsymbol{Y} - \boldsymbol{\phi}\boldsymbol{\theta}\|^2. \tag{5}$$

Eq. (5) is not appropriate enough for modeling the $\dot{\mathrm{V}}\mathrm{O}_2$ or $\dot{\mathrm{V}}\mathrm{CO}_2$ response as the input of the system is a square signal and the measurement of the output contain various artifacts. Therefore, a regularization term is added to Eq. (5) in order to regularize the estimation and guarantee the effectiveness of the obtained model [12]. As the impulse response is modeled as a zero-mean Gaussian process, the priori information, which is contained in the kernel matrix, is introduced in the identification process to assign a covariance [13]. Therefore, the regularization term $J_R(\boldsymbol{\theta})$, which belongs to a Reproducing Kernel Hilbert Space (RKHS) $\mathscr{H}$, is defined as Eq. (6):

$$J_R(\boldsymbol{\theta}) = \boldsymbol{\theta}^{\mathrm{T}} \boldsymbol{P}^{-1} \boldsymbol{\theta}, \tag{6}$$

where $\boldsymbol{P}$ is a suitable kernel matrix.

The priori information in kernel matrix $\boldsymbol{P}^{-1}$ could help the estimated $\hat{\boldsymbol{\theta}}$ provide a better and smoother result when compared to least square estimation [10].

Based on our previous work [9], the Stable Spline (SS) kernel which is shown in Eq. (7), demonstrates a better performance than the other kernels based on the aspects of accuracy, sensitivity, stability and smoothness.

$$P(i,j) = \frac{c}{2} e^{-\beta min(i,j)} - \frac{c}{6} e^{-3\beta max(i,j)}, \tag{7}$$

where $c \geq 0$, $0 \leq \beta < 1$.

The SS kernel inherits all the approximation capabilities of the spline curve by construction [10], [14] and is intrinsically stable. The SS kernel represents the least committing priors when smoothness and stability is the sole information on $\boldsymbol{\theta}$.

Then the estimation of $\boldsymbol{\theta}$ is obtained as:

$$\hat{\boldsymbol{\theta}} = \arg \min_{\boldsymbol{\theta} \in \mathbb{R}^m} \left(\|\boldsymbol{Y} - \boldsymbol{\phi}\boldsymbol{\theta}\|^2 + \gamma \boldsymbol{\theta}^{\mathrm{T}} \boldsymbol{P}^{-1} \boldsymbol{\theta} \right), \tag{8}$$

where γ is a positive scalar.

Finally, the Eq. (8) could be adapted as Eq. (9):

$$\hat{\boldsymbol{\theta}} = \left(\boldsymbol{P}\boldsymbol{\phi}^{\mathrm{T}}\boldsymbol{\phi} + \gamma \boldsymbol{I}_{\boldsymbol{m}} \right)^{-1} \boldsymbol{P}\boldsymbol{\phi}^{\mathrm{T}}\boldsymbol{Y}, \tag{9}$$

where $I_m \in \mathbb{R}^{m \times m}$ is an identity matrix with the dimension of $m \times m$.

B. EXPERIMENT

Two experiments, namely "stairs experiment" and "treadmill experiment", are conducted in this research due to the different command. The UTS Human Research Ethics Committee (UTS HREC 2009000227) approved these experiments and informed consent was obtained from all participants before commencement of data collection. The set-up of the two experiments, hardware and the application interface are shown in Fig. 1.

For the two experiments, the $\dot{\mathrm{V}}\mathrm{O}_2$ and $\dot{\mathrm{V}}\mathrm{CO}_2$ were both divided by the weight (kg) for each participant to exclude the impact of the participant's weight on breath information. The normalized $\dot{\mathrm{V}}\mathrm{O}_2$ and $\dot{\mathrm{V}}\mathrm{CO}_2$ are recorded as $\dot{\mathrm{V}}_{\mathrm{d}}\mathrm{O}_2$ and $\dot{\mathrm{V}}_{\mathrm{d}}\mathrm{CO}_2$. In total, 35 untrained (non-athletes) and healthy (no records of motor skill disorder, cardiac-respiratory disorder or related medications history) male participants are recruited in this study. According to different purposes, the participants are assigned randomly to the two experiments in the aspects of age, height and $\mathrm{HR}_{\max}$ to ensure the fairness of the comparison between the two kernel parameter selection methods. The treadmill experiment is designed for identifying the relationship between the exercise phase and $\dot{\mathrm{V}}\mathrm{O}_2$ or $\dot{\mathrm{V}}\mathrm{CO}_2$ by the non-parametric model. In order to guarantee universality and compatibility, the sample size of 20 participants is chosen in the treadmill experiment. The stairs experiment is designed for selecting the appropriate parameter in the non-parametric model, then the remaining 15 participants are assigned to the stairs experiment.

FIGURE 1. Scenes of experiments, the equipment and application interface.

1) STAIRS EXPERIMENT

The stairs experiment is about HR maintaining between the range of 60% to 80% of the participants' $\mathrm{HR}_{\max}$ during the stairs exercise. In this experiment, $\mathrm{HR}_{\max}$ is calculated as [15]:

$$\mathrm{HR}_{\max} = 205.8 - 0.685 \times \text{age} \tag{10}$$

A self-designed mobile application is used to collect the various information from 15 participants, including HR, steps, and direction (upstairs or downstairs). The mobile phone is placed on the ankle of participants. The Inertial Measurement Unit (IMU) data could represent the direction of the movement. Meanwhile, the breath data including $\dot{\mathrm{V}}_{\mathrm{d}}\mathrm{O}_2$ and $\dot{\mathrm{V}}_{\mathrm{d}}\mathrm{CO}_2$ are collected by a portable gas analyzer- Cosmed $K4b^2$ (Cosmed, Italy) [16]. The basic biological information of the participants is shown in Table 1.

The participants are instructed to go upstairs and downstairs continuously for 12 minutes. The experiment starts by collecting data while going upstairs. Once the participants' HR exceeds 80% of $\mathrm{HR}_{\max}$, they are instructed to go downstairs. When their HR is under 60% of $\mathrm{HR}_{\max}$, they are asked to go upstairs again. The $\dot{V}O_{2\max}$ is monitored to observe the ventilatory threshold $VT1$ and lactate threshold $VT2$ [17]–[19]. There will be $2-4$ complete periods (one full period is from the beginning of upstairs exercise to the

TABLE 1. Information about the 15 participants in stairs experiment.

Information	Age (*year*)	Height (*cm*)	Mass (*kg*)	HR_{max}	$60\%HR_{max}$	$80\%HR_{max}$
Mean	29.60	172.60	83.00	185.40	111.10	148.30
Standard Deviation	7.60	3.40	5.39	5.25	4.28	3.35

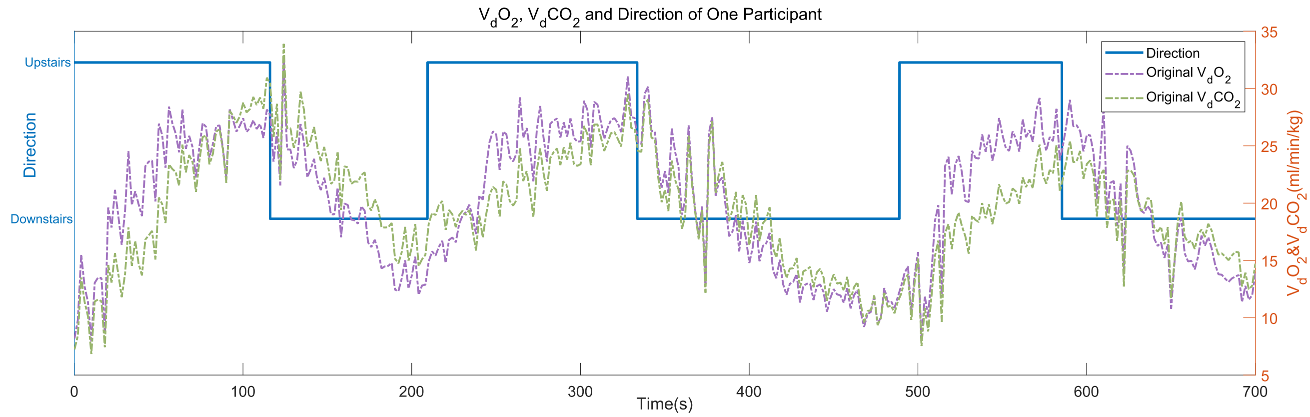

FIGURE 2. Measured $\dot{V}_dO_2$, $\dot{V}_dCO_2$ and exercise direction of one participant during stairs experiment.

TABLE 2. Information about the 20 participants in treadmill experiment.

Information	Age (*year*)	Height (*cm*)	Mass (*kg*)	HR_{max}	$60\%HR_{max}$	$80\%HR_{max}$
Mean	46.40	176.60	91.20	173.60	104.16	138.88
Standard Deviation	5.68	4.40	11.37	5.53	3.32	4.42

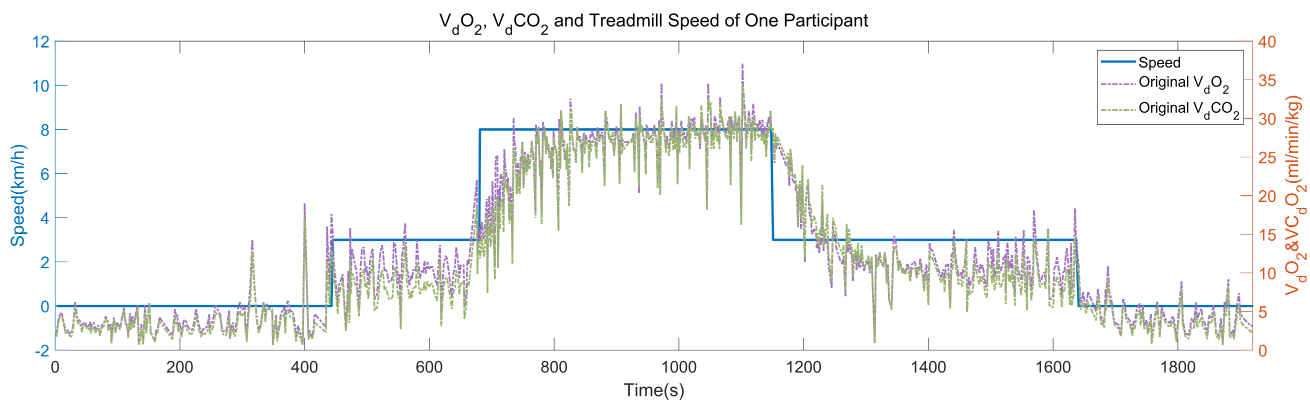

FIGURE 3. Measured $\dot{V}_dO_2$, $\dot{V}_dCO_2$ and speed of one participant during the treadmill experiment.

end of downstairs exercise) for an entire exercise routine for all participants. The direction of the exercise is described as 1 when the participants are ascending (go upstairs), and 2 when descending (go downstairs). A sample of the direction and measured $\dot{V}_dO_2$ and $\dot{V}_dCO_2$ from one participant is shown in Fig. 2. The $\dot{V}_dO_2$ and $\dot{V}_dCO_2$ are filtered by median filter to remove the artifacts before identification. This experiment ensures a continuously changing input (direction) and output ($\dot{V}_dO_2$ and $\dot{V}_dCO_2$) for guaranteing a sufficient stimulation in kernel parameter selection part.

2) TREADMILL EXPERIMENT

The treadmill experiment is about a jogging exercise on treadmill. The $\dot{V}_dO_2$ and $\dot{V}_dCO_2$ data is also recorded by the $K4b^2$ when the 20 participants, who are not the same individuals as the stairs experiment, are jogging on the treadmill following an exercise protocol. The physical information of the participants is shown in Table 2.

The protocol of this experiment is shown in Fig. 3. The participants first walk with the speed of 3 km/h for four minutes, and then run at 8 km/h for eight minutes, followed by another walk at 3 km/h for eight minutes before stopping.

C. PARAMETER SELECTION

The parameter of the kernel is a vital part to determine the estimated model structure. Two different methods are applied to select the parameter c and β in SS kernel as shown in Eq. (7). The first method is numerical simulation and the second method is parameter tuning in the stairs experiment. The most appropriate parameter is selected to the non-parametric modeling for the treadmill experiment.

We apply the fit ratio NRMSE (normalized root mean square error) to obtain the goodness of fit of estimated output, which is represented as follow:

$$\text{NRMSE} = \left(1 - \frac{||\hat{Y}_N - Y_N||}{||Y_N - \text{mean}(Y_N)||}\right), \tag{11}$$

where N is total number of sampling, Y_N is the real data (reference) and $\hat{Y_N}$ is the estimated Y_N.

1) PARAMETER SELECTED FROM NUMERICAL SIMULATION

Our simulation begins with a first-order system to describe the relationship between the O_2 uptake or CO_2 output and the treadmill speed according to the description of $\dot{V}_dO_2$ and $\dot{V}_dCO_2$ in previous study [9], [20] as shown in Eq. (12):

$$V(t) = V_0 + R_A[1 - e^{-(t-T_D)/\tau}]. \tag{12}$$

where $V(t)$ is the $\dot{V}_dO_2$ or $\dot{V}_dCO_2$ at time t, V_0 is the initial value of $\dot{V}_dO_2$ or $\dot{V}_dCO_2$, R_A is the response amplitude, T_D is the time delay, and τ is the time constant.

Thus, the system is set as Eq. (13):

$$Y(s) = \frac{K}{Ts+1}U(s), \tag{13}$$

where K that follows the uniform distribution U(5, 15) is the steady gain, and T which follows U(15, 25) is the time constant.

The input of the system $U(s)$ is set to be the same trend as the stairs experiment to ensure a similar stimulation. The simulated output $Y(s)$ is polluted by a Gaussian white noise with 1 dB Signal-Noise Ratio (SNR). The sampling time is selected as 1 second.

The parameter c and β in Eq. (7) of the SS kernel mentioned in Section II-A are the primary targets of tuning. After tuning the parameter in the simulation [11], we selected the following combination of c = [100 200 300] and β = [0.95 0.987 0.99] and the samples of the IR model are shown in Fig. 4. After the statistics of fitness and the observation of IR smoothness and stability, the best combination is $c = 200$ and $\beta = 0.987$.

2) PARAMETER TUNING FROM STAIRS EXPERIMENT

As mentioned above, the continuously changing data in stairs experiment could ensure a enough stimulation for the system. Therefore, the identification for $\dot{V}_dO_2$ and $\dot{V}_dCO_2$ in the stairs experiment is aimed to select the most appropriate parameter and compare the selection process. We choose one period from each participant to do the identification. The identification is also conducted by the non-parametric method. After the preliminary range selection, we find that when β is in the range of $0.9975 - 0.999$, the fitness shows better results. Then we make further statistics about the fitness of the parameters in this range. As the exercise phase changes continuously during the stairs exercise, the

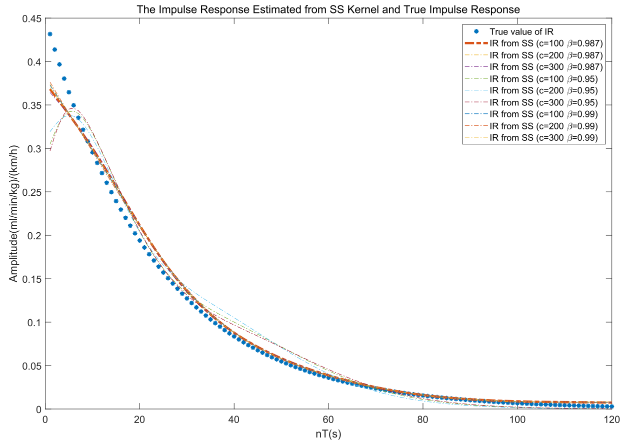

FIGURE 4. Impulse response from SS kernel compared to the true value of impulse response in the simulation.

TABLE 3. The fitness of different parameter β for $\dot{V}_dO_2$ and $\dot{V}_dCO_2$ identification in the stairs experiment of ten participants.

Sub.	Fitness of Estimated $\dot{V}_dO_2$				
β	**0.9975**	**0.9978**	**0.998**	**0.9985**	**0.999**
1	68.91%	73.16%	75.34%	76.91%	76.40%
2	66.64%	66.74%	66.53%	65.42%	63.85%
3	81.95%	82.11%	82.30%	82.00%	81.16%
4	76.89%	79.36%	80.36%	80.46%	79.41%
5	65.30%	69.06%	71.94%	76.95%	76.98%
6	63.07%	64.16%	64.69%	64.69%	63.27%
7	75.83%	76.25%	76.11%	75.17%	73.34%
8	76.66%	77.49%	77.58%	76.70%	74.85%
9	66.27%	66.29%	66.36%	67.85%	69.41%
10	63.84%	65.42%	66.26%	66.79%	65.41%
Amount	0	2	2	1	2
Sub.	Fitness of Estimated $\dot{V}_dCO_2$				
β	**0.9975**	**0.9978**	**0.998**	**0.9985**	**0.999**
1	73.26%	73.82%	74.66%	75.93%	75.45%
2	66.68%	66.46%	66.29%	65.21%	63.42%
3	80.69%	80.91%	81.23%	81.67%	81.18%
4	81.55%	81.68%	81.70%	81.19%	80.23%
5	76.96%	77.90%	78.26%	77.99%	76.41%
6	64.45%	64.72%	64.68%	64.25%	63.04%
7	77.51%	77.30%	76.98%	76.29%	74.50%
8	77.15%	77.92%	78.12%	77.29%	75.32%
9	66.30%	66.30%	66.31%	67.85%	69.45%
10	67.58%	67.16%	66.93%	65.8%	64.54%
Amount	3	0	4	2	1

* "Sub." means the ten participants.
** "β" means the value of the parameter β.
*** "Amount" indicates the number of participants which achieve the highest fitness when using this value of parameter-β.

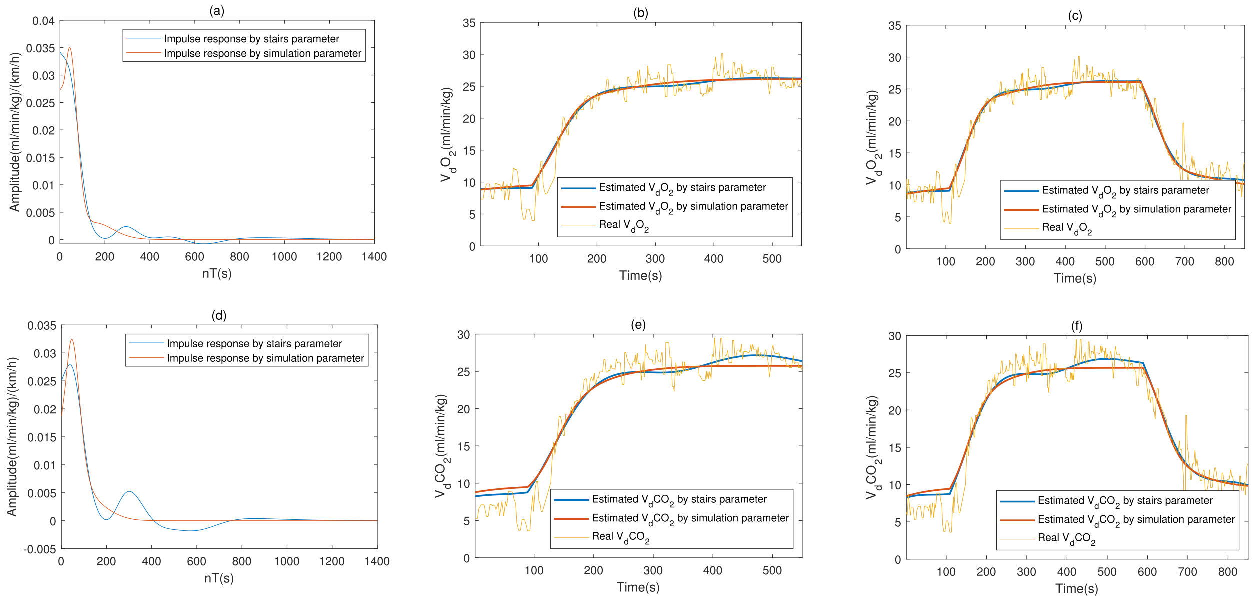

FIGURE 5. Impulse response and estimated output comparison by parameter selected from stairs experiment and simulation of participant A. (a) Impulse response for estimated $\dot{V}_dO_2$. (b) Real and estimated $\dot{V}_dO_2$ in half period. (c) Real and estimated $\dot{V}_dO_2$ in full period. (d) Impulse response for estimated $\dot{V}_dCO_2$. (e) Real and estimated $\dot{V}_dCO_2$ in half period. (f) Real and estimated $\dot{V}_dCO_2$ in full period.

performance of some participants is not steady enough for the identification part and the results are not in line with the common situation. To guarantee the effectiveness of the parameter selection, the results from the participants that the fitness is below 60% are excluded. Hence, Table 3 represents the fitness level of stairs experiment identification results (10 out of 15 participants, whose fitness exceeds 60%). The results from these 10 participants are chosen to construct the model for the kernel parameter selection. Finally, we decide that $c = 200$ which is same with the simulation, and $\beta = 0.998$, which is marked as red in Table 3, according to its university for most participants' $\dot{V}_dO_2$ and $\dot{V}_dCO_2$.

D. STATISTICAL ANALYSIS

In order to verify that the fitness of the models is significantly different between the two parameter selecting approaches, the statistical analysis is necessary. After the fitness of identification results from treadmill experiment by different parameter selecting approaches is calculated, the histogram and normal probability of the fitness is plotted in Matlab to determine whether the fitness follows a normal distribution. As the results of normality shows, the Wilcoxon Rank Sum test is used because the fitness does not follow normal distribution. Generally, $p < 0.05$ means $h = 1$, and the fitness is considered as statistically significant.

III. RESULTS

In this section, the identification results about the $\dot{V}_dO_2$ and $\dot{V}_dCO_2$ in the treadmill experiment are discussed. The comparison between estimation fitness when using the parameter β from stairs experiment and simulation are also be presented.

We applied the non-parametric model identification method for both the ascending period and entire period of $\dot{V}_dO_2$ and $\dot{V}_dCO_2$ in the treadmill experiment. The impulse response and the estimated results (ascending period and entire period) of $\dot{V}_dO_2$ and $\dot{V}_dCO_2$ from one representative participant are shown in Fig. 5. Based on the IR in these two figures, the model is more flexible when the parameter β from stairs experiment is used. Furthermore, the estimated output is closer to the real output both for $\dot{V}_dO_2$ and $\dot{V}_dCO_2$ during both ascending and entire period.

As the parameter β in the non-parametric model is selected by two different approaches-tuning from stairs exercise and selecting from numerical simulation, the performance of these two selection approaches need to be investigated. Hence, after the non-parametric model with the selected parameters is applied in the treadmill experiment during the onset period and the full onset-offset period, the fitness between real output and estimated output is calculated. The comparison of the estimated fitness is displayed in Fig. 6 to show the performance of the two parameter selection approaches. The figures illustrate that all the output estimation fitness when using the parameter β from the stairs experiment is higher than using the parameter β from the simulation for both $\dot{V}_dO_2$ and $\dot{V}_dCO_2$. The fitness improvement by kernel parameter from stairs experiment compared with parameter from numerical simulation are summarized in Table 4.

The histogram and the normal probability of the estimation fitness for $\dot{V}_dO_2$ and $\dot{V}_dCO_2$ in treadmill experiment during half or one period are shown in Fig. 7. The estimation fitness is acquired by using different parameter selection approaches (selecting from numerical simulation and tuning from stairs

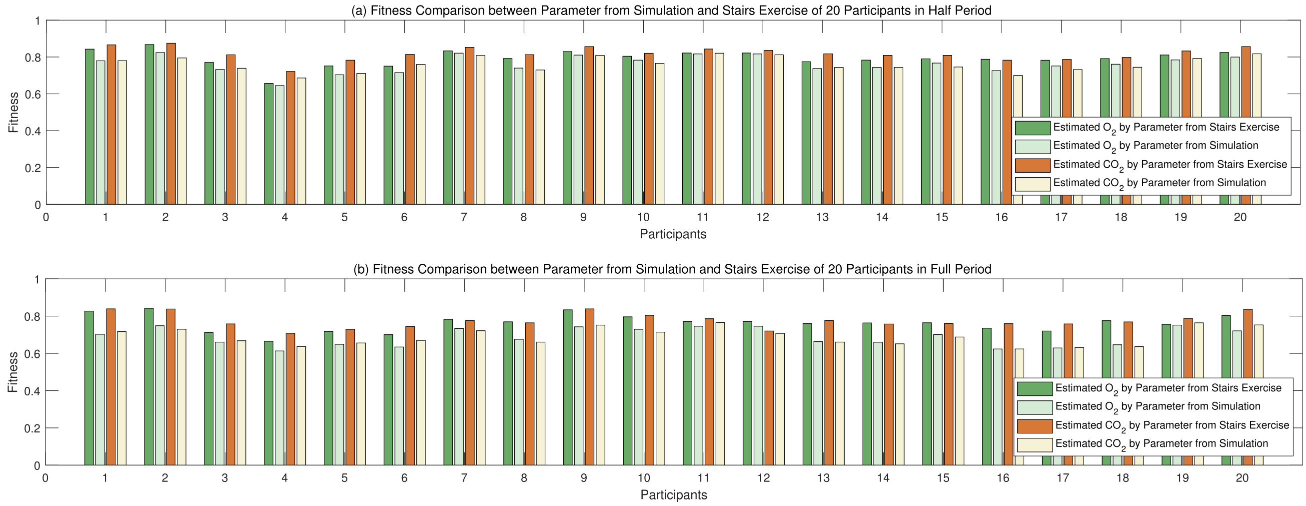

FIGURE 6. **Estimated $\dot{V}_dO_2$ and $\dot{V}_dCO_2$ fitness comparison by parameter selected from stairs experiment and simulation of 20 participants in (a) Ascending period and (b) Full period.**

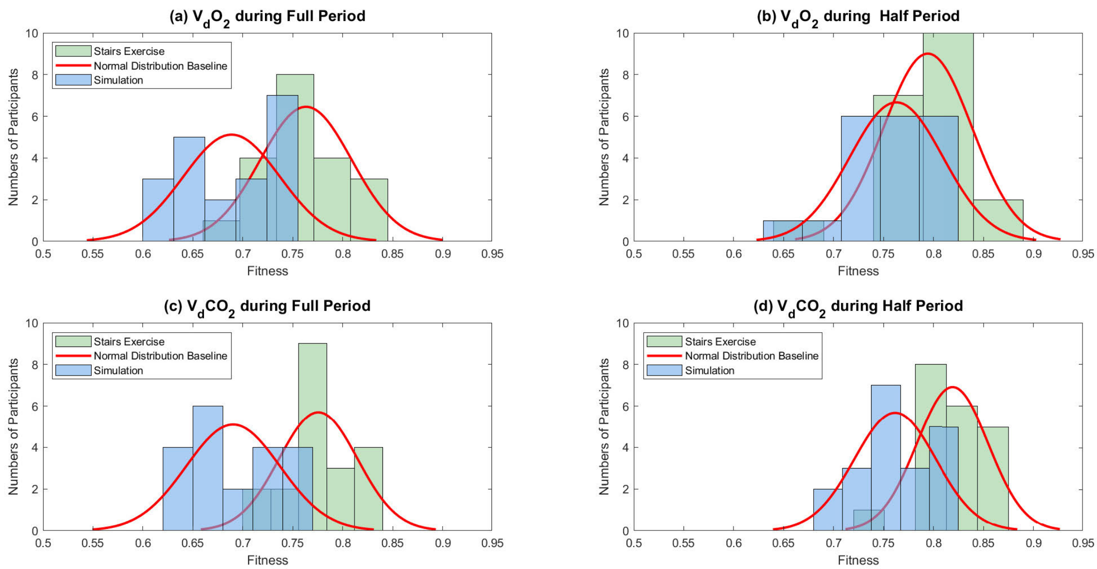

FIGURE 7. **Histogram of estimation fitness by parameter selected from stairs experiment and simulation of 20 participants. (a) $\dot{V}_dO_2$ Fitness in full period. (b) $\dot{V}_dO_2$ Fitness in half period. (c) $\dot{V}_dCO_2$ Fitness in full period. (d) $\dot{V}_dCO_2$ Fitness in Half Period.**

TABLE 4. **The improvement of estimation fitness using kernel parameter from stairs experiment.**

Comparison	Improvement
$\dot{V}_dO_2$ in Half Period	4.18%
$\dot{V}_dO_2$ in One Period	11.00%
$\dot{V}_dCO_2$ in Half Period	7.63%
$\dot{V}_dCO_2$ in One Period	12.60%

TABLE 5. **Wilcoxon rank sum test of estimation fitness comparison when using β from simulation and stairs experiment.**

Output	p value	h
$\dot{V}_dO_2$ in Half Period	$p=1.55^{-2}$	h=1
$\dot{V}_dO_2$ in One Period	$p=5.24^{-5}$	h=1
$\dot{V}_dCO_2$ in Half Period	$p=1.44^{-4}$	h=1
$\dot{V}_dCO_2$ in One Period	$p=8.60^{-6}$	h=1

exercise) and demonstrate that the identification fitness is commonly higher when using the parameter selected from the stairs exercise than numerical simulation. The Wilcoxon Rank Sum test is applied because the estimation fitness does not follow the normal distribution. As the Wilcoxon Rank Sum test results shown in Table 5, all four outputs satisfy with the general condition, indicating that the results is statistically significant.

IV. DISCUSSION

A. THE PERFORMANCE OF NON-PARAMETRIC MODEL

The advantage of using the non-parametric modeling method when the system structure is uncertain as opposed to the classical linear modeling method [8], [21], [22], was presented in various ways. In previous studies, the commonly used method for modelling $\dot{V}_dO_2$ or $\dot{V}_dCO_2$ is a mono-exponential function [20], [23] and the parameters are determined by nonlinear least-squares regression. Julian *et al.* [24] studied the effects of the constraints in this traditional mono-exponential model. The importance of the constraints is also demonstrated in our study. Furthermore, The impulse response of the model generated by the two approaches illustrates the characteristics of a non-first-order system and this is demonstrated directly in Fig. 5. By contrast, the IR model using the parameter β from the stairs experiment fluctuates to a greater extent than the simulation. The oxygen uptake identification results of the stairs experiment using the linear model from the work of Jan *et al.* [22] showed a mean fitness of 62.5%. The fitness results using the non-parametric model in this paper, as shown in Table 3, are 6.21% higher. As the non-parametric model is applied, the amount of information is sufficient to fully utilize the priori information and this ensures the complexity of the IR model for estimation. The priori information in the kernel provides the support to estimate the structure of the system. In addition, the regularization term contains the kernel matrix which eliminates the possibility of overfitting.

The structure of the system under the protocol in our experiments is of higher complexity than the first-order system or time-invariant system and this is demonstrated by the identification results. In the numerical simulation part for parameter selecting, we acquired the β value under the assumption that the system is a first-order system based on the previous study [20]. Our previous study [9] also revealed that in the single ascending or descending period, the system is close to a first-order system, but there are still exceptions because of the individual difference. However, in this research, the physiological information contains two periods of ascending ($0 - 3 - 8$ km/h) or a full period with ascending and descending ($3 - 8 - 3$ km/h). This means that the information is not enough to determine the structure of the system which is more complicated than a single onset or offset period. Hence, ideal results can be achieved by using the non-parametric model, and results demonstrate that the system is no longer a first-order system or that it may vary when the period changes. The higher improvement in terms of estimation in one period, as shown in Table 4, also demonstrates that the non-parametric model is effective for the complicated system.

B. THE PARAMETER OF KERNEL MATRIX IN NON-PARAMETRIC MODEL

The parameter of the kernel matrix in the non-parametric model should be selected carefully since the regularization term within the kernel matrix plays a significate role in identification. For the impulse response estimation, the kernel $\boldsymbol{P}$ possesses a large condition number which leads to numerical problems, such as failure or inaccuracy of the Cholesky decomposition of $\boldsymbol{P}$ [11]. Compared with the numerical computation method in Gulob and Van Loan's study [25], this problem could be tackled in an active way based on our priori information about $\boldsymbol{P}$ in the impulse response estimation. If the parameter of the kernel that controls the decaying rate of $\boldsymbol{P}$ are very small, the kernel may have a large condition number. Under this circumstance, the extra constraint on these parameters should be enforced in order to guarantee the tolerably large condition number which is designed to avoid numerical problems. To achieve such a goal, the selected value of parameter β in kernel matrix from the stairs experiment is compared with the value chosen from the simulation to create a more appropriate constraint. The extra constraints limit the search region of the parameter. The research of Chen, Ohlsson et al [26] demonstrates that the extra constraints do not cause the performance issues in the regularized least squares estimation.

The fitness of identification results is higher in Fig. 6-Fig. 7 when using the parameter β from the stairs experiment, which is also demonstrated by the fitness comparison in Table 4. As well, the estimated output in Fig. 5 shows that the estimation when using the parameter β from the stairs experiment observes some slight changing trends in relation to the $\dot{V}_dO_2$ or $\dot{V}_dCO_2$. The reason for the higher fitness is that sufficient stimulation is important for the modeling. Data from the stairs experiment ensures that there is sufficient input, which is a continuously changing step response for the system. The direction switching strategy guarantees the randomness of the input. The selection of the participants' HR_{max} from the 60% to 80% range is designed to ensure a maximum range of stimulation. The uncertainty of a random input could make the information matrix substantial in a limited time. The input signals from the stairs experiment are of enough intensity and duration. The dynamic relationship between the exercise phase and $\dot{V}_dO_2$ or $\dot{V}_dCO_2$ during the stairs experiment is obvious enough because of their continuously changing nature. By contrast, the frequently changing treadmill speed can make the participants uncomfortable. However, this shortcoming does not exist in the stairs experiment. Accordingly, this is the reason for using the stairs experiment for the parameter selection.

V. LIMITATIONS OF THE STUDY

The parameter selection procedure for the stairs exercise was achieved by tuning in a certain range. In future works, this part could be selected adaptively.

VI. CONCLUSION

To summarize, we applied the kernel-based non-parametric method to identify the dynamics of $\dot{V}_dO_2$ and $\dot{V}_dCO_2$ responses to treadmill speed. In order to guarantee a sufficient stimulation for modeling, the parameter β selected from the stairs experiment is constructed and compared with β

selected from simulation. The data from the stairs experiment is collected by a self-designed application, and this experiment protocol ensures a continuously changing input and physiological signal. The results demonstrate the benefits of using the non-parametric modeling method when the system structure cannot be described by a simple model. The fitness comparison also illustrates that when using the parameter β from the stairs experiment, the estimation results are better than the ones from the simulation. This is because the switching protocol provides a sufficient level of random stimulation and the stairs experiment provides continuously changing data.

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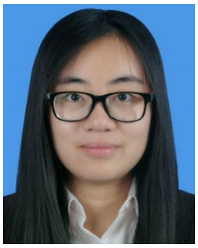

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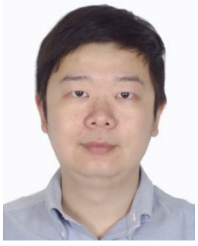

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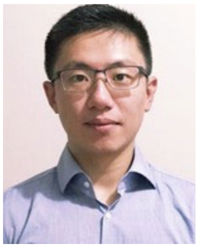

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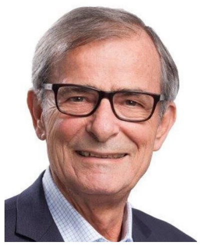

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