An Exercise-Driven Heart Rate Statistical Process Model

Yuanjing Yang, Lianye Ji, Hanxiao Wu, Jiankang Wu
Sensor Networks and Applications Joint Research Center (SNARC)
Graduate University, Chinese Academy of Sciences, Beijing, China
E-mail: {yangyuanjing09, wuhanxiao10}@mails.gucas.ac.cn, {jilianying, wujiankang}@gucas.ac.cn

Abstract—Relationship between heart rate and exercise is useful for health diagnosis and monitoring. A statistical process model is proposed to model relationship between heart rate and activity. Multiple models are built and each of them is corresponding different phase of heart-rate change due to activity, such as drift and recovery phases. Subject-dependant parameters of each model are estimated using LMS method. An integral model for full heart rate dynamic are built by further fusing those model based on model probability. The variant models for both heart predication given activity intensity and real time heart rate filtering are also presented. The multi-phase model is more consistent with physiological process and the statistical nature of it makes it more robust. And more importantly, it is the first model which also describes the variability of heart rate changes with exercise, besides kinetics.

Keywords-kinetic cycle; fusion model; non-ideal activity context;

I. INTRODUCTION

It’s well known that heart rate is regulated by Autonomic Nerves System (ANS) and heart rate is not constant even under completely stationary conditions. Its variance (namely HRV) is also regulated by ANS which are heavily affected by daily activities. During exercise, the cardiovascular system increases the delivery of blood and oxygen to working muscles as the metabolic demand increases, resulting in an increase in heart rate (HR) and stroke volume [1]. The increase of heart rate is positively correlated to the activity intensity. On the contrary, several studies have proved that HRV will decrease during exercise [2]. The decrease is believed related to vagal withdraw, which dominate the HRV background at rest.

Studying and modeling of heart rate (HR) response during exercise have been carried out by a number of researchers. Brodan [3] and Hajek [4] modeled the HR response, both during exercise and recovery phases. Their models consist of feed forward and feedback components [5] and are reliable for short-duration exercises but are not sufficient for explaining responses to long-duration exercise. The exercising HR response was modeled by a Hammerstein system, a system that consists of a static nonlinearity cascaded at the input of a linear system. Again, their models were derived for describing HR responses for short-duration exercise. Besides modeling, they also studied the control and regulation of the HR response during exercise.

Some previous studies have modeled the HR with monoexponential or biexponential equations [6]. HR was expressed as the sum of a baseline value plus one or two first order e-function with time delay [7]. However, in those models the work load values were not directly considered by the calculation of the heart rates. Those studies were conducted with constant work load, moderate or heavy exercise intensities. They did not describe the dynamic responses of HR to the varying workloads quantitatively. Furthermore, the cardiac drift effect was not taken into consideration. Another study has shown that while exercising at a HR which is 5% below the HR at the ventilatory threshold, the work load has to be reduced by approximately 17% (from about 220 to 183 watt) over time, although the HR was kept relatively stable (176-180 bpm). Cardiac drift is accentuated by numerous factors such as dehydration and head stress and therefore an important factor for the HR modeling.

Lu Wang, and Steven W. Su once built a nonlinear multi-element cardiovascular model [8]. In 2007, they established a highly simplified nonlinear multi-element cardiovascular model based on their previous work [9]. The simplicity of the structure of their new model makes it suitable as a starting point to build up more complex models to reflect cardiovascular characteristics, especially during the condition of moderate exercise. In their study, the previous model was examined to have the ability to reproduce stroke volume (SV), cardiac output (CO) blood pressure (BP) and total peripheral resistance (TPR) recorded from normal subjects by training its three parameters. Then they improved the model by incorporating a new physiological interaction, making it capable of estimating another important physiological parameter - metabolic demand.

Above mentioned studies all established their models by mathematical method. In fact, heart rate is a random signal with statistical properties. In this paper, we propose a heart rate model fused with real-time activity information. We consider heart rate under one single intensity activity can be modeled as a complete dynamic cycle which can be applied for multi-intensity complex exercise context. The input of this model is activity intensity and the output is heart rate. Firstly we cut one complete heart rate cycle into four phases and established model for each one respectively whose parameter is different to each subject and can be obtained by data training. Then the whole model of the complete heart rate cycle can be obtained based on the procedure of random signal processing.
II. DATA COLLECTION EXPERIMENTS

The data that we use to establish the model were all acquired using our own context-aware heart monitor called uCare. It is a Holter-like wearable heart monitor device, which can record 3-lead ECG signals and 3-axis acceleration signals, and store them into a micro SD card. The device can be worn by the subjects around the chest which is shown in figure 1.

![Figure 1. The device and its wearing](image)

The experiment was conducted in gym with controlled conditions. This experiment was conducted on the treadmill in the gym with temperature 20°C. The experiment procedure included multiple consecutive resting and running sessions with controlled stable intensity.

10 young healthy men aging from 23-30 participated in the experiments. The subjects were 7 men and 3 women, with body mass index (BMI) from 18-27, and with no history or clinical signs of cardiovascular or pulmonary disease. Candidates were not taking any kind of medication and did not show abnormal blood pressure or ECG patterns. Besides, before and during the experiment, the subjects didn’t drink water.

The experiment was carried out for at least three times as for every subject. Each time, the subjects were asked to select three different speeds according to their own physical qualities. The three speeds were supposed to be the light, middle and intense intensity for the each subject respectively. While most of male subjects chose 5miles/hour, 7 miles/hour, and 9 miles/hour, most of female subjects chose 3miles/hour, 5miles/hour, and 7miles/hour. Each of the running session with one chosen speed lasted for 10 minutes following with 15 minutes resting. During the resting session, the subjects were almost totally static without any significant movements. Besides, they were also asked to have a rest for a quarter before and after the whole procedure respectively.

III. DATA PREPROCESSING

The data collected in above mentioned experiment are further processed to obtain heart rate data and activity intensity.

A. ECG Processing and Heart rate Computation

The ECG signal is noisy and interfered by baseline drift and artifacts caused by movements. A wavelet based QRS detection method described in [10] by Rudnicki and Strumillo is used. The method is carried out by following steps:

1) The wavelet transform is used to remove baseline wandering, noise, movement artifacts of ECG signals and extract QRS complex relevant features.

2) An auto threshold is applied to detect QRS complex. The positions of peaks of QRS complexes are marked as positions of R waves.

3) Additionally, the so-called refractory period is taken into account, when the RR intervals are examined and some irrational detection results are corrected. More importantly, the RR interval based premature beats detection is conducted.

The final result of this processing stage is Normal-to-Normal RR intervals. At last, the intervals between successive normal R waves are computed to obtain heart rate data which is shown in figure 2.

![Figure 2. the calculated heart rate in the above experiment](image)

B. Activity intensity

The activity intensity has linear relationship with total fluctuation area (TFA) of acceleration signals [11]. Therefore TFA is used to indicate intensity level. Higher the TFA value means higher the activity intensity. Defining \(a_{k,i}\) as acceleration signal of axis k at time i, and N as length of a analysis time window, TFA is defined by

\[
F_A = \sum_{k=1}^{3} \sqrt{\sum_{i=1}^{N} (a_{k,i} - \bar{a}_k)^2}, \quad k = \{1, 2, 3\}
\]

\[
TFA = \sum_{k=1}^{3} F_A^k
\]

(1)

One example of intensity of the experiment referred before is shown in figure 3. In the figure, the raw z-axis acceleration signal is also plotted which is to demonstrate that the intensity is positively related to the acceleration signal. Therefore, it can be used to stand for activity intensity level.
IV. EXERCISE-DRIVEN MULTI-MODEL

A. The statistical properties of heart rate

A lot of experiments have proved that even the activity intensity is unchanged, RR interval is not invariant. Its value fluctuates around a specific value affected by activity intensity, health condition and other personal factors. The RR intervals and its distribution under various intensity activities is shown in figure 4.

B. Dynamic cycle of heart rate

A complete heart rate cycle when people do single intensity activity is shown in figure 5.

C. The model of parameter $\sigma$

It’s already known that HRV which reflects the variance of heart rate decreases during exercise and is negatively related to activity intensity. Therefore we model the parameter as:

$$\sigma_k = \sigma_{rest} \times k / INT$$

(2)

The parameter $k$ can be obtained by data training.

The parameter $\mu$ is much more complex which will be modeled as followings.

D. The establishment of segmentation model of parameter $\mu$

Because different phase of the heart rate shows different change feature. Therefore we establish model for the rise period, drift period and recovery period respectively firstly according with their various shapes.

According to the fundamental physiological principles, the heart rate response to the intensity during exercise is generally expressed by the equation

$$HR(k) = HR_{rest} + \Delta HR(k)$$

(3)

where $k$ is sampling step, $HR(k)$ is the heart rate value in bpm, $HR_{rest}$ is the heart rate value before the exercise start, and
\(\Delta HR(k)\) is the change of heart rate according to the intensity at sampling step \(k\). Due to the fact that the dynamic of the HR responses to the intensity may differ under different phases of the heart rate, \(\Delta HR\) is modeled separately.

1) The rising phase:

Under moderate exercise intensity, the energy production mainly relies on the aerobic pathways. It is well known that HR increases linearly with increasing exercise intensity over a wide range up to sub maximal intensities [12]. In this stage, heart rate will increase rapidly due to the change of activity conditions. It takes very short time for heart rate increases to the target value, usually one or two minutes. Figure 6 shows the rising phase of heart rate under low, middle and high level intensity activity.

![Figure 6. the rising phase of heart rate under low, middle and high level intensity activity](image)

The figure shows that the slope is seldom influenced by activity intensity which is because the time is too short and the increasing speed is quickly enough. However, it still can be seen that heart rate will increase more rapidly with the activity intensity increases. Therefore, under moderate exercise intensity, \(HR_{\text{rise}}\) is modeled as

\[
\Delta HR_{\text{rise}}(k) = a_1 \times \text{INT}(k - 1) + a_2 \times \Delta HR(k - 1) + \omega_1(k - 1)
\]

(4)

with \(\Delta HR(k - 1)\) is the change of heart rate at sampling time \(k-1\), \(\text{INT}(k-1)\) is the activity intensity at the moment, \(\omega_1(k - 1)\) is the noise.

2) The drift phase:

With exercise lasted, the subject was adapt to the activity intensity, the heart rate will not increase so rapidly but show a drift phenomenon which is resulted from the complex slow-acting effects, for example, the hormonal systems, the peripheral local metabolism, the increase in body temperature, and the loss of body fluid due to sweating and hyperventilation. Because of the cardiac drift effect, the heart rate can drift upwards by up to 20 bpm during exercise over time, despite unchanged activity intensity and steady or decreasing plasma lactate concentrations. Figure 7 shows the drift phase of heart rate under low, middle and high level intensity activity.

![Figure 7. the drift phase of heart rate under low, middle and high level intensity activity](image)

The exact amount of the heart rate drift depends on the exercise duration and actual intensity. Besides, the drift has a trend of getting smaller with time lasting which is fit to characteristic of exponential function. It’s clearly acknowledged that the drift amount will bigger with higher intensity. Therefore the final value of the drift amount is positively related with intensity. Besides, the drift speed is also positively related with intensity. Thus the cardiac drift is modeled by equation 5:

\[
\Delta HR_{\text{drift}}(k) = a_3 \times (1 - \exp(-T_\lambda k / \tau)) \times \text{INT}(k - 1) + \omega_2(k - 1)
\]

(5)

In (5), \(T_\lambda\) means the exercise duration at the sampling step \(k\), \(\omega_2(k - 1)\) is the noise.

3) The recovery phase:

Until this phase, there is no input of activity intensity, and the heart rate will decrease and finally return to a static value. At the beginning of this stage, the heart rate recovered to some extent in a short time. But it will take a long time to make the heart rate recover to the heart rate at rest time. Figure 8 shows the recovery phase of heart rate under low, middle and high level intensity activity.
Figure 8. the recovery phase of heart rate under low, middle and high level intensity activity

The recovered time has relationship with personal conditions, the activity intensity and lasted time.

\[ \Delta H_{\text{rec}}(k) = a_4 \times \exp[-a_5 \times (k - a_6)] + \omega_3(k - 1) \]  

(6)

E. The complete heart rate model

To model the continuous heart rate change due to a series of exercise status, we need to combine above independent models together.

The rising phase and drift phase are corresponding different intensity level, thus we can use a switch “\( k \)” according to the intensity to transit the models.

However, because during the rise and drift phase are corresponding to the same intensity level, this transition reflects the transition between different ANS status of heart rate regulation. Sympathetic nervous system (SNS) accelerates heart rate while para-sympathetic nervous system (PNS) decreases the heart rate. HRV shows the balance of SNS and PNS and is dominated by the vagul-related nervous in PNS. During exercise, the activity of SNS increases while the activity of PNS decreases regularly. Thus the transition is believed to be smoothly. Therefore, we establish the statement transformation equation as:

\[ \Delta H(k) = \alpha(k) \times \Delta H_{\text{rise}}(k) + \omega_3 \times \Delta H_{\text{drift}}(k) \]  

(7)

In the equation, \( \alpha \) is the likelihood of the rising model and \( 1-\alpha \) is the likelihood of the drift model. It’s known that \( \alpha \) will decrease with time passing, which means that the probability of one heart rate point according with the rising model should decrease with time and oppositely the probability of it in line with the drift model should increase. We suppose that \( \alpha \) is linear as following equation show:

\[ \alpha(k) = b_1 \times \alpha(k - 1) + b_2 \]  

(8)

Finally, we can obtain the whole model as follows:

\[ H(k) = H_{\text{rest}} + \alpha(k) \times H_{\text{rise}}(k) + (1-\alpha(k)) \times H_{\text{drift}}(k) + \omega(k) \times \Delta H_{\text{rec}}(k) + \omega(k-1) \]  

(9)

in (10), \( \Delta H_{\text{rise}} \), \( \Delta H_{\text{drift}} \), \( \Delta H_{\text{rec}} \) is calculated by (4), (5), (6) respectively. \( \omega(k-1) \) is the noise.

V. RESULTS

A. Parameter estimation

1) The parameter estimation of segmentation models

In the data collection experiment, nine sets of data are obtained to estimate the parameters. The data are preprocessed to obtained activity intensity and corresponding heart rate. Therefore, parameter estimation is equal to data fitting.

In this article, the parameters of segmentation models are obtained by nlinfit method provided by MATLAB. Figure 9-11 are the result of rising, drift and recovery model fitting:

![Figure 9. the result of rising model fitting](image)

![Figure 10. the result of drift model fitting](image)
2) The parameter estimation of complete model

The parameters \( \{ b_1, b_2 \} \) of fusing model \( \alpha(k) \) are estimated based on kalmen filter and probability theory. The heart rate in transition segment is processed in the following steps:

1) Suppose that the value belongs to rising phase, the heart rate value \( h_r_1 \) is calculated by equation (4) using the previous heart rate value and activity intensity.

2) Suppose that the value belongs to drift phase, the heart rate value \( h_r_2 \) is calculated by equation (5) using the previous heart rate value and activity intensity.

3) Calculate the distance between \( h_r_1 \) and real heart rate as \( D_1 \), while that between \( h_r_2 \) and real heart rate as \( D_2 \).

4) \( \alpha(k) \) is shown in equation:

\[
\alpha(k) = \frac{D_1}{D_1 + D_2}, \quad 1 - \alpha(k) = \frac{D_2}{D_1 + D_2}
\]  

(10)

5) A sequence of \( \alpha \) are obtained. The parameters \( \{ b_1, b_2 \} \) are obtained by curve fitting using least square method (LSM). Therefore, \( \alpha(k) \) is determined. The complete model of the whole heart rate cycle is determined.

Figure 12 shows the result of fusing model fitting:

B. Error analysis

According our requirement, during the date collection experiment, the subject must run with constant speed. But in fact, there exits fluctuations in their running speeds although the speed of the treadmill are programmed. Besides, fitting is just a approximation. The error rate is calculated with the following equation:

\[
e^2 = 100 \times \sqrt{\frac{\sum [HR(k) - \overline{HR(k)}]^2}{N}}
\]  

(11)

where \( HR(k) \) is the actual observed value of heart rate at sampling time \( k \), and \( \overline{HR(k)} \) is the heart rate calculated with equation (9) according intensity and previous values. The error rate of ten subjects is shown in table 1.

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VI. Conclusions

In this study, a statistical process model is proposed to model relationship between heart rate and activity. Multiple models are built and each of them is corresponding different phase of heart-rate change due to activity, such as drift and recovery phases. Subject-dependant parameters of each model are estimated using LMS method. An integral model for full heart rate dynamic are built by further fusing those model based on model probability. The variant models for both heart predication given activity intensity and real time heart rate filtering are also presented. The multi-phase model is more consistent with physiological process and the statistical nature of it makes it more robust. And more importantly, it is the first model which also describes the variability of heart rate changes with exercise, besides kinetics. And the model has been used to filter heart rate sequence under given activity conditions and the results have been evaluated. Furthermore, the model can also be used to heart rate prediction.
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REFERENCES


