Monitoring and Prediction of Exhaustion Threshold during Aerobic Exercise Based on Physiological System using Artificial Neural Network

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Abstract

Exhaustion or extreme of fatigue is the highest condition of body performance during exercise. This state presents an optimum energy to execute by an athlete before their level of fitness reduced and required the recovery process. The purpose of this study is to monitor and predict an exhaustion threshold from three physiological systems; respiratory, cardiovascular and muscular by using artificial neural network. A developed wearable device to measure those parameters is needed for the data collection in fatigue experiment protocol. Then, it was separated into its category and filtering that signal to remove all unwanted noise in the database. Statistical feature extraction was executed for divided into five levels of exhaustion to implement supervised machine learning method. A mathematical model for prediction was developed in artificial neural network based on the data obtained from the exhaustion threshold. This model can facilitate the coach and athlete to monitor their level of exhaustion as well as prevent from the severe injury due to over exercise.

Keywords: Aerobic Exercise; Exhaustion; Wearable; Machine Learning Method

Abbreviations: RR: Respiratory Rate; HR: Heart Rate; EMG: Electromyogram; ANN: Artificial Neural Network; SVM: Support Vector Machine; MR: Multilinear Regression

Introduction

Movements in sports are the main criteria of the physical exercise, and it is a combination of muscle contraction and the human skeleton which reflected in musculoskeletal systems. However, the most affected movements were muscle activation due to aerobic exercise such as walking; jumping and running required a repetitive motion. Muscle contraction during aerobic exercise is related to the oxygen consumption in order to endure the repetition of movement in a period of time. Therefore, it depends on the demand and supply by the muscle and oxygen respectively. Based on the blood circulation in the systemic and pulmonary system, oxygen (O_2) was exchanged with carbon dioxide (CO_2) at two places; in the respiratory system by alveolus membrane tissue [1] and bundle of muscle tissue. These organs were functioned to ensure that volume of oxygen capacity in the physiological is equal to remain the balance condition. Fatigue is a maximum condition of exercise when the level of oxygen was decreased while the lactic acid produced greater. This lactic

acid production will reduce the ability of muscle to contract as performing the physical exercise [2].

Monitoring the level of fatigue by focused to the muscle contraction based on the oxygen consumption not represent the whole physiological activity during aerobic exercise. It is significant to consider another system into account for the measurement such as respiratory and cardiovascular systems. Hence, there are some previous researchers were associated fatigue or exercise to the heart rate variability [3,4], blood pressure [5], respiratory rate [6], electromyogram [7,8], and mechanomyogram [9]. On the other hand, there has been in recent years, an increasing amount of literature on detecting fatigue by using the EMG monitoring with signal processing analysis [10-13], computer control [14] and statistical [15]. However, in terms of oxygen circulation to supply to working muscle, the other physiological systems such as respiratory and cardiovascular or called as cardio respiratory systems are

corresponded to the physical exercise [16]. Therefore, physical exhaustion is not exclusively due to weakness of muscle, but it can be affected to the other parameters as well. Additional consideration of parameters into account will help to investigated exhaustion in wide angle of views and details.

Traditionally, the physical exhaustion is related to the muscle fatigue. However, combination of input parameters or data fusion in identified exhaustion is lacking in the previous research due to enlarging its uncertainty. Therefore, this proposed study objectively to predict an exhaustion level by reducing its uncertainty through the machine learning method. This approach was hypothesized that exhaustion is reflected in the blood or oxygen circulation rate during aerobic exercise. By using machine learning method, it will predict accurately the level of exhaustion based on the threshold. Consequently, this approach beneficial to the athlete and coach to monitoring their level of exhaustion and prevent from the maximum condition that can be led to severe injury.

Research Framework

Overall structure of this proposed study was designed in the Figure 1 including the theory and procedure that will be conducted to accomplish the objective. It illustrates the parameters involved in monitoring fatigue based on selected physiological measurement using the wearable device. Three parameters identified as a main contribution in this study, which is respiratory rate (RR), heart rate (HR) and electromyogram (EMG). It also represents for the three physiological systems considered in blood circulation, which indicates oxygen consumption by the muscle contraction. A wearable device of each measurement was developed to monitor and detect fatigue by providing an alarm to warn the user during performing an exercise. There are five (5) indicators that differ from their level of fatigue initiated with status very light and end to the maximum intensity. Since the fatigue level of each person varies due to human uncertainty, a set of data during fatigue as a threshold is needed to categorize based on control group criteria such as BMI, ages, and sports.
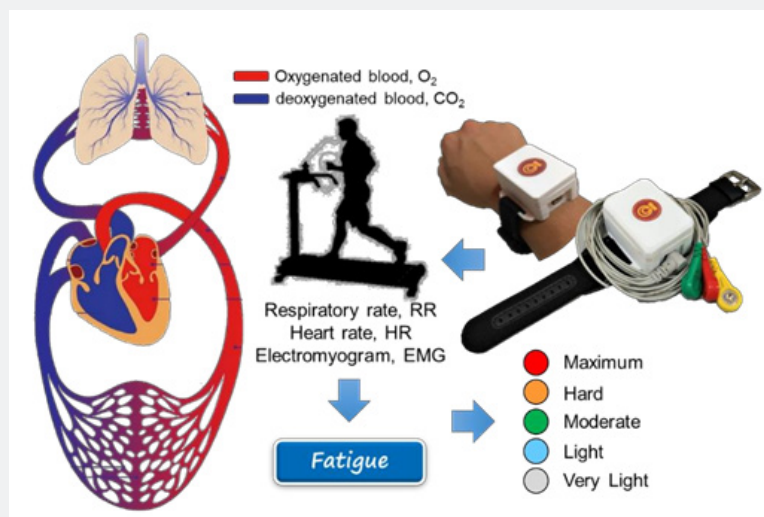
Figure 1: Parameters involved in each organ to determine the fatigue level.

By using the machine learning method, it could be a good way to predict the level of fatigue in supervised approach. This technique is believed to be an objectively assessment by mathematical model to the response promptly and reduce the time consumption. It was proved when applied for localized muscle fatigue [7], hand grasp movements [17], predict sudden cardiac death based on heart rate variability [18], and estimating upper extremity movements [19].

On the other hand, wearable device functioned to evaluating exhaustion by those selected parameters in analyzing data collection. Therefore, Figure 2 indicates the schematic diagram for the data analysis processes in predicting exhaustion zones in real-time monitoring. It has three stages; 1) pre- processing, 2) post-processing and 3) displaying exhaustion zones. In pre-processing stage, three signals from three different signals were measured, which are respiratory rate, heart rate, and electromyogram. The raw signals filtered and removed the artefacts that interrupting the real signals by using signal processing method. These measurements were then collected and stored in the temporary database prior to move to the next stage for analysis. In this level as well, the databases were kept in a statistical formatting in order to make it easier for the feature extraction procedure. Next stage is the post-processing procedure for the analysis using the machine learning method which is artificial neural network (ANN). There is another approach that can be used such as support vector machine (SVM) and Multilinear Regression (MR) to predict and accomplished this purpose, but it was just about the result's accuracy. Finally, the results from the machine learning method will present the prediction of the exhaustion level by indicating based on status of zones range over sequence from very light to the maximum.
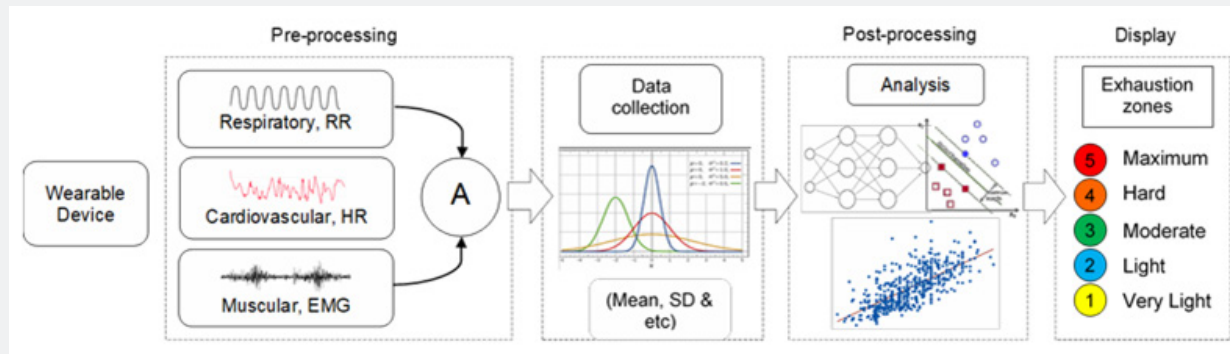
Figure 2: Data analysis process for the machine learning method.

In addition, this method for developing an algorithm was translated into the mathematical model that can be integrated with the current wearable device for the real-time monitoring assessment. For the future recommendation, this device will be upgraded with the intelligent user interface mechanism to be incorporated with the Android apps on the smart phone. Furthermore, visual tools were contained for the output alarm to alert the user such as color of LED and tone of the buzzer. All of these implements will enhance the wearable device to the smart operating function.

Conclusion

This study is promising to monitor and predict an exhaustion threshold by using the wearable device incorporating machine learning method. The problem of the vigorous movements among the athlete or sports can be solved by implemented this algorithm in terms of signal processing. Meanwhile, this small size of device attached to the body tightly will not bothering their movement on the field.

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