A Portable Multiparameter Assessment System for Real-Time Monitoring of Exercise-Induced Fatigue

Chi-Chun Chen[1*], Chung-Chen Teng[1]

ABSTRACT

In this study, an assessment system integrating multiple physiological parameters was developed to investigate the exercise-induced fatigue of users who exercise at home. Because the majority of home-use exercise monitoring systems monitor only one single physiological parameter, these systems cannot accurately assess the user's overall fatigue level. The proposed system monitors various parameters, including heart rate variability and electromyography, transmits its readings to a remote server for analysis, and uses fuzzy logic to assess the level of exercise-induced fatigue. Therefore, this system allows users to adjust their exercise intensity in a timely manner to prevent exercise-induced muscle injuries or discomfort. Comparison with the participants' perceived fatigue levels revealed that the proposed system has 80% accuracy.

Keywords: Electromyography (EMG), exercise-induced fatigue, heart rate variability (HRV)

1. Introduction

With advancements in medical technology, quality of life, and healthcare accessibility, health awareness has increased on a global scale. However, heavy workload and changes in eating habits often cause individuals to neglect their health. Although the optimal prescription for a healthy life is adequate exercise, the incidence of exercise-induced injuries, discomfort, and sudden death has been increasing [1, 2]. These events can be typically attributed to insufficient warmup, excessive mental strain, or exhaustion.

When an individual exercises, their heartbeat changes as a result of their engagement in a physical activity. Therefore, heart rate (HR) can be used to assess an individual's physical condition. In particular, heart rate variability (HRV), a parameter that represents changes in heartbeat intervals, is an index that indicates the ability of the autonomic nervous system to control and maintain balance in physical and organ functions [3]. Because both the sympathetic and the parasympathetic nervous systems are affected when an individual engages in exercise, the changes in HRV that correspond to changes in the sympathetic and parasympathetic nervous systems reflect the state of the autonomic nervous system during exercise [4]. Macor *et al.* [5] reported that, at rest, athletes exhibited greater high-frequency (HF) power in their HRV compared with nonathletes. However, during exercise, both athletes and nonathletes exhibited substantially reduced low-frequency (LF) and HF power in their HRV. In a physiological study, Baselli *et al.* [6] reported that the HRV of individuals who exercised to the point of fatigue had clearly low HF and LF peaks and LF/HF ratio, suggesting a reduction in the activity of the sympathetic and parasympathetic nervous systems. Mattioli and Araújo [7] reported that individuals who engaged in exercise had progressively decreasing total power (TP) in their HRV. Overall, these results indicated that HRV-related time–frequency parameters are key indices in the evaluation of motor functions.

Surface electromyography (EMG) is frequently used to evaluate muscle fatigue [8, 9]. Exercise-induced muscle fatigue, which is a temporary reduction in muscle contraction strength as a result of physical activity, can be monitored through changes in surface EMG (SEMG) parameters in the affected site [10]. In an EMG time-domain analysis study, DeVries [11] reported that when knee extensors and elbow flexors were used during static sedentary work, the root mean square (RMS) amplitudes of the EMG increased with time. In a frequency-domain analysis study, Paavo and Per [12] reported that when their participants engaged in knee extension exercise at a constant angular velocity until muscle fatigue, the SEMG frequency spectra of their quadriceps shifted toward lower frequencies, and these muscles exhibited progressively decreasing mean power frequencies (MPFs). In a study comparing changes in the SEMG frequency spectra of biceps brachii muscles and quadriceps femoris muscles, Sadoyama and Miyano [13] reported that, after the development of fatigue following isometric contractions, both muscle types exhibited gradually decreasing MPFs and leftward-shifting SEMG frequency spectra, which were particularly noticeable in the biceps brachii muscles. In a study of isokinetic knee

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contractions, Tomoki and Toshihiro [14] observed and reported that, after the development of fatigue, the muscles performing this exercise exhibited a linearly decreasing SEMG median frequency (MF).

Generally, muscles are categorized as either fast-twitch or slow-twitch muscles. Fast-twitch muscles are powerful but fatigue rapidly. Therefore, once fatigue sets in, slow-twitch muscles become responsible for strength output. This phenomenon causes the EMG frequency spectrum to shift toward lower frequencies (because the motor units in slow-twitch muscles tend to have a low frequency), which in turn decreases the MF and MPF. As shown in Fig. 1, electrical activity (EA), a parameter in the time domain, and MF, a parameter in the frequency domain, can be combined through the joint analysis of EMG spectrum and amplitude (JASA) to determine the level of muscle fatigue depending on EMG signal intensity and frequency distribution [15].

Although physiological monitoring devices are widely used in household settings, these devices are incapable of determining the overall level of physical fatigue because they can monitor only one physiological parameter. In this study, an integrative system capable of monitoring multiple physiological parameters, wirelessly transmitting its readings to a remote server for analysis, and using fuzzy theory was proposed. By integrating multiple physiological parameters into a single all-inclusive parameter, this system allows for reasonably estimating exercise-induced fatigue. The quantified estimate is then sent back to the user from the remote server, thereby allowing the user to adjust their exercise intensity and avoid overtraining (Fig. 2).

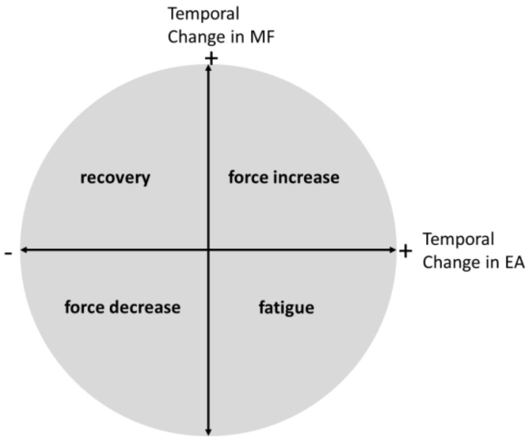


Figure 1. Relationship between EMG and frequency spectrum changes.

2. Methodology

This study is divided into three parts. The first part involves the development of a wireless physiological multiparameter system with low power consumption. This system is portable (i.e., small and lightweight) and can extract physiological information, such as electrocardiography (ECG) and EMG signals. The second part involves the development of an intelligent body area network platform equipped with a 2.4-GHz wireless transmission module for the wireless transmission of physiological signals, thereby eliminating the inconvenience caused by transmission cables. The third part involves the development of a remote management system, which was designed to enable the remote analysis of physiological parameters by trained professionals and the transmission of feedback to the user to prevent fatigue-induced injuries.

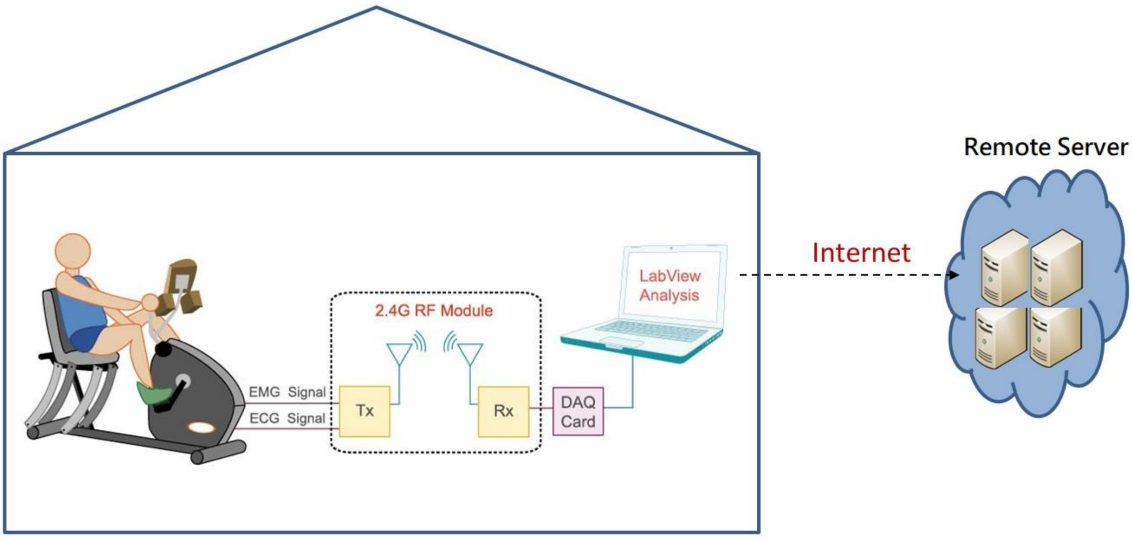


Figure 2. Portable wireless multiparameter system for the assessment of exercise-induced fatigue.

2.1. System Architecture

As shown in Fig. 3, the development of the proposed system involved a hardware configuration phase and a physiological parameter computation phase. The hardware configuration included a power circuit, a wave filter, an ECG module, an EMG module, a wireless transmission and reception module, and a data acquisition interface. Physiological parameter computation was performed as follows. Original readings were first extracted from the data acquisition card and then computed in h the Lab's Virtual Instrumentation Engineering Workbench (LabVIEW), including the time-domain and frequency-domain changes of HRV and EMG signals.

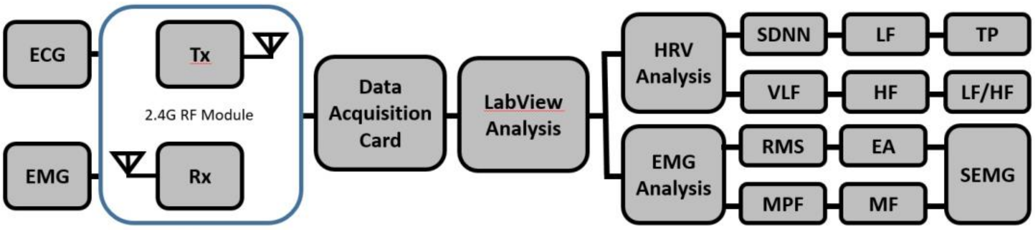


Figure 3. Block diagram for the proposed measuring system.

2.1.1. Design of the ECG Measurement Circuit

After the electric potential difference was measured in the electrode pads, the signals were preamplified using an AD620 instrumentation amplifier. Because the ECG signals of interest were between 0.05 and 100 Hz, the signals within this range were amplified, whereas those outside this range were attenuated. A low-pass filter (100 Hz) and a high-pass filter (0.05 Hz) were then used to remove signals of unwanted frequencies. The remaining signals were output after passing through a noninverting amplifier (Fig. 4).

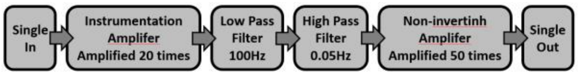


Figure 4. Block diagram for ECG measurement.

2.1.2. Design of the EMG Measurement Circuit

EMG signals were acquired by measuring the changes in action potential in activated muscle fibers. To measure the changes in electric potential in the muscles, electrode pads were attached on the gastrocnemius and soleus muscles, with a reference electrode placed on the ankle. However, the readings were extremely low and required preamplification by an instrumentation amplifier (AD620). Because the EMG signals of interest were between 100 Hz and 1 KHz, the signals within this range were amplified, and those outside this range were attenuated. A low-pass filter (1 KHz) and a high-pass filter (100 Hz) were then used to remove signals of unwanted frequencies. The remaining signals were output after passing through a noninverting amplifier (Fig. 5).

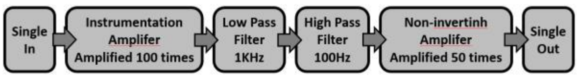
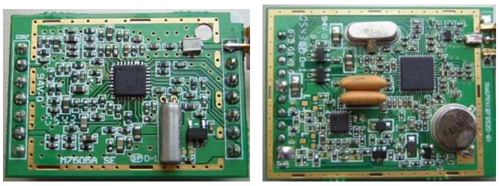


Figure 5. Block diagram for EMG measurement.

2.1.3. Intelligent Body Area Network Platform

As a result of the development of biosensors in medical applications, wireless sensor networks, which have been originally used in military, scientific, and civic disciplines, have been integrated into sensor networks in close proximity to the human body. These networks are called wireless body area networks (WBANs). Optimally, a wireless network should feature self-configuration, fault tolerance, security, and self-repair capabilities. Therefore, intelligent node application is well suited for WBANs. Generally, WBANs are characterized by a large number of sensor nodes or actuators deployed in a small area; a large bandwidth requirement and network architecture; the ability to connect with adjacent networks; network nodes that indefinitely remain active in low-duty-cycle sleeping mode; wireless sensors that "know" what to measure; multihop routing of data packets, which means data packets are transmitted through multiple wireless nodes; no fixed network topology, which means all nodes in the network can be moved; and a low-power transmission protocol. In this study, a 2.4-GHz wireless broadband audiovisual transmission system from RichWave (Taipei City, Taiwan) was used as a WBAN. As shown in Fig. 6, the system consists of a 2.4-GHz frequency modulation (FM)/frequency-shift keying (FSK) transmitter (RTC6701), a 2.4-GHz FM/FSK receiver (RTC6711), and a dual-channel volume control integrated circuit unit (RTC6721).



Transmission module Reception module

Figure 6. B RW67RX-SA01 wireless transmission and reception module.

2.1.4. Remote Network Management

In this study, remote network management was achieved using Simple Network Management Protocol (SNMP). Because SNMP conforms to the currently established network, communication, and management standards, hardware incompatibility is not a concern provided that all the hardware of the system conforms to these standards. As shown in Fig. 7, SNMP primarily consists of a network management system (NMS), an agent, and a management information base (MIB). The NMS is responsible for managing the network, collecting data from various agents, and generating simple statistical diagrams. The Multi Router Traffic Grapher is a commonly used tool for generating diagrams from the data collected through SNMP. The agent is a software program installed on a managed device. It collects data from the device and transmits these data to the NMS. The NMS periodically requests data from the agent through polling. As an alternative, when an emergency occurs, the agent actively reports to the NMS through trap messages. The MIB then hierarchically displays the attributes of the managed device. By using a standardized MIB, the NMS can manage various devices made by different manufacturers.

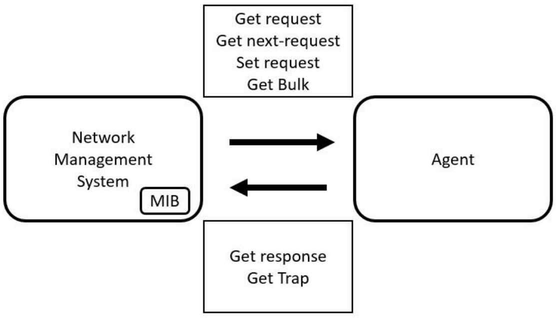


Figure 7. SNMP model.

2.2. Experimental procedures

Ten individuals aged 20–30 were invited to participate in the experiment, which involved riding a stationary bike with a progressively increasing intensity, as per the recommendations of the World Health Organization (Table I). A wireless transmission module was used to send the physiological signals of the participants to a remote server. These signals included ECG and EMG (calf muscles) signals, which were recorded for 3 min at each of six load levels. Various indices were used to determine whether any of the participants exhibited signs of fatigue. The experimental procedures were as follows:

Step 1: Place the measurement modules on a participant.

Step 2: Adjust the pedal and seat positions to reduce physical exertion.

Step 3: Check system operation and signal waveforms.

Step 4: Activate the system and take readings.

Step 5: Start at load level 1 and take readings for 3 min. Progressively move to load level 6, with 30 s of rest between each load level.

Step 6: Send the readings to the remote server for physiological parameter calculation.

TABLE I

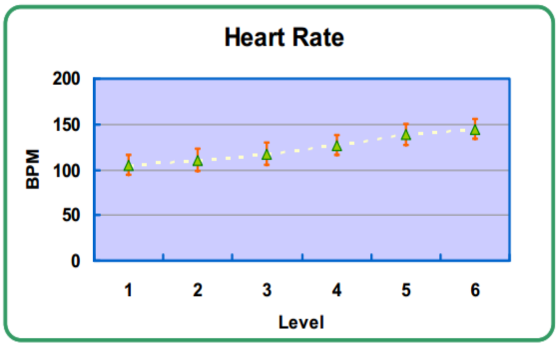
PROGRESSIVELY INCREASING LOAD LEVELS

Load level	**Load intensity (W)**	**Test time (min)**	**Pedaling speed (rpm)**
1	100	3	70
2	150	3	70
3	200	3	80
4	250	3	80
5	300	3	80
6	350	3	80

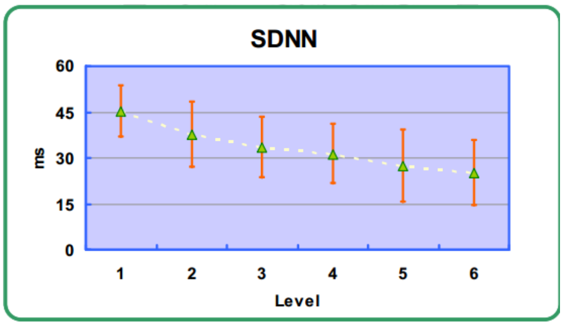
3. Results and Discussion

3.1. ECG Analysis

Fig. 8 presents the results of the ECG analysis. As shown in Fig. 8(a), HR increased with increasing load level and fatigue. In the HRV time-domain analysis, the standard deviation of NN intervals, a key parameter in HRV evaluations, decreased with increasing load level, as shown in Fig. 8(b). In the HRV frequency-domain analysis, very low frequency (VLF), a key parameter that represents sympathetic activity, decreased with increasing load level or with the onset of fatigue, as shown in Fig. 8(c). LF, which reflects the regulation of both the sympathetic and the parasympathetic nervous systems, decreased with increasing load level or with the onset of fatigue, as shown in Fig. 8(d). HF, which reflects parasympathetic activity, decreased with increasing load level, as shown in Fig. 8(e). The LF/HF ratio, which reflects the balance of autonomic activity, decreased with increasing load level or with the onset of fatigue, indicating a gradual malfunctioning of autonomic activity, as shown in Fig. 8(f). Because muscle fatigue was observed in all six parameters, the effectiveness of the experimental design in inducing muscle fatigue was confirmed.



(a)



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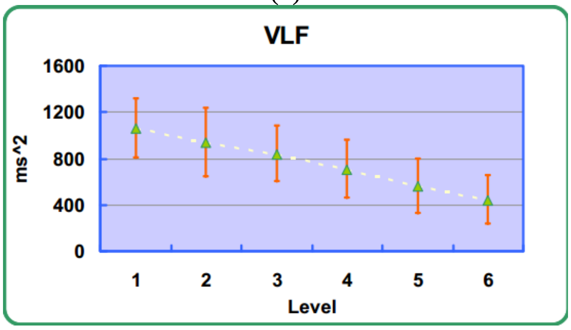

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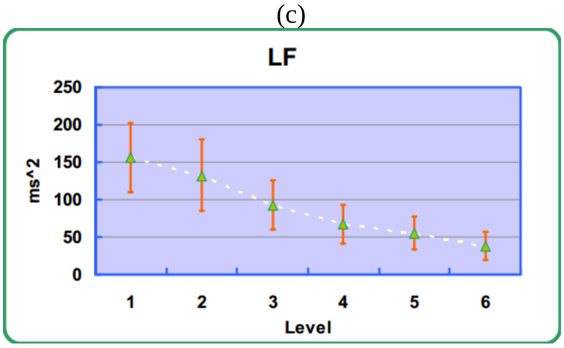

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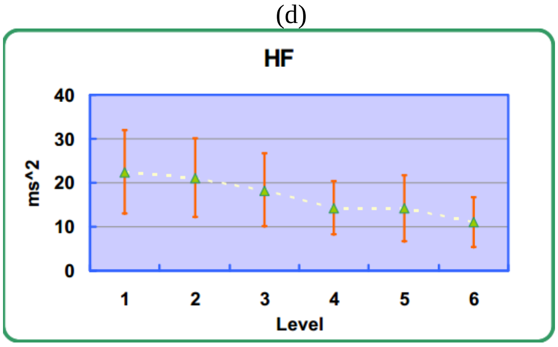

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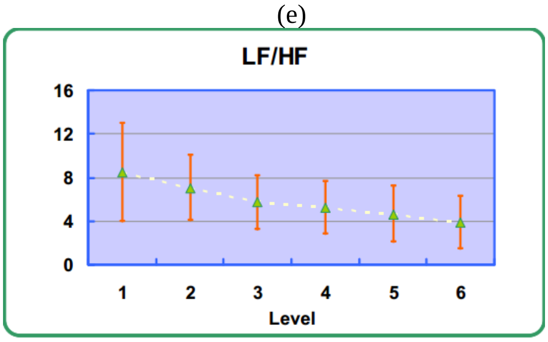
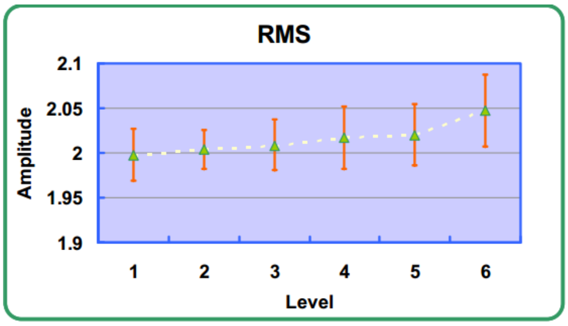


(f)

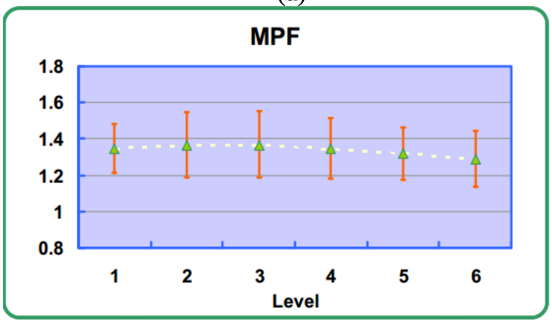
Figure 8. ECG analysis.

3.2. EMG Analysis

Figs. 9–11 present the results of the EMG analysis. As shown in Fig. 9(a), the RMS increased with increasing load level or fatigue level. However, the MPF decreased with increasing load level or fatigue level, as shown in Fig. 9(b). These results are consistent with the literature [11, 12].



(a)



(b)

Figure 9. EMG analysis.

Fig. 10 compares the EMG power spectra of load levels 1 and 6. When the load level (and hence the level of fatigue) increased, the spectrum shifted toward lower frequencies. This trend is consistent with the results of [13].

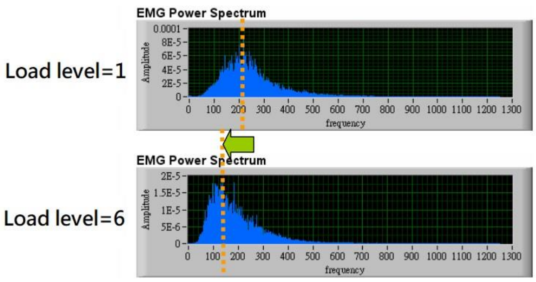


Figure 10. EMG power spectra of load levels 1 and 6.

As shown in Fig. 11(a), at load levels 1 and 2, the EA and MF concurrently increased, indicating that all participants were still increasing their strength output (i.e., muscle fatigue has not yet set in). However, as shown in Fig. 11(b), at load levels 3 and 4, the participants' muscle conditions started to change. In other words, some participants were still increasing their strength output, whereas others started to show signs of decreased muscle strength or even fatigue. As shown in Fig. 11(c), at load levels 5 and 6, the participants completely fatigued and lost their muscle strength. Hence, according to the distribution of JASA coordinates, the participants' muscles gradually demonstrated signs of fatigue as the load level increased.

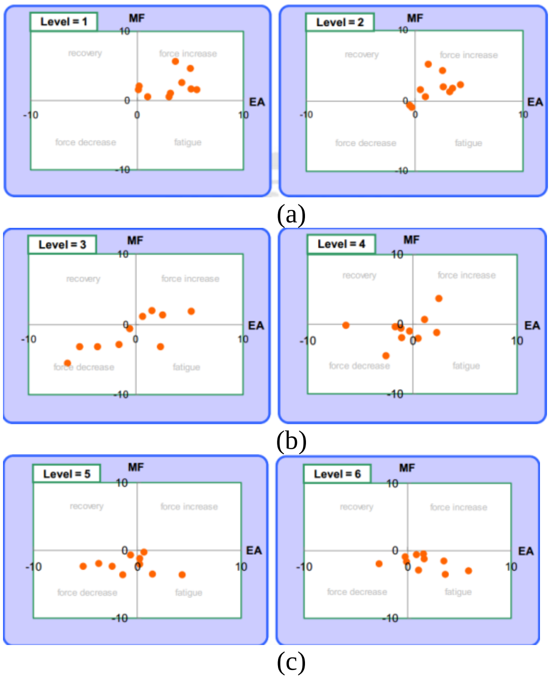


Figure 11. Distribution of JASA coordinates at load levels 1–6.

3.3. Integration of Multiple Parameters

To achieve greater accuracy and robustness in the assessment of exercise-induced fatigue, multiple parameters were integrated using a fuzzy logic method. A fuzzy model was designed using the Fuzzy Toolbox of MATLAB (MathWorks, Natick, MA USA). As shown in Fig. 12, the model consisted of four components: a fuzzification component, a rule base component, an inference engine component, and a defuzzification component. The parameters that were identified as relevant, namely SNDD, LF, LF/HF, and RMS, were used as the input. Comparison of the assessment results of the fuzzy-integrated parameter and the participants' perceived fatigue levels revealed that the assessment was accurate for eight out of the ten participants and inaccurate for the remaining two.

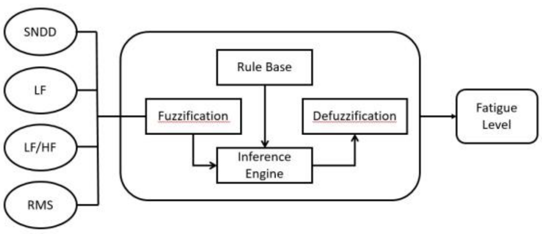


Figure 12. Multiple parameter integration system.

4. Conclusion

In this study, HRV and EMG parameters were integrated to develop a wireless portable assessment system for exercise-induced fatigue for home use. The results confirmed the relevance of HRV and EMG parameters for exercise-induced fatigue. When these parameters were integrated using fuzzy logic, an accuracy of 80% was achieved. In future studies, in addition to increasing the sample size to improve system practicality, other computation methods should be evaluated to enhance system accuracy.

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