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A Neuro-Fuzzy Fatigue-Tracking and Classification System for Wheelchair Users

WENFENG LI[1], (Senior Member, IEEE), XINYUN HU[1], RAFFAELE GRAVINA[2], (Member, IEEE), AND GIANCARLO FORTINO[2], (Senior Member, IEEE)
[1]School of Logistics Engineering, Wuhan University of Technology, Wuhan 430063, China
[2]Department of Informatics, Modeling, Electronics and Systems, University of Calabria, 87063 Rende, Italy

Corresponding author: Xinyun Hu (huxinyun@whut.edu.cn)

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ABSTRACT With the elderly and disabled population increasing worldwide, the functionalities of smart wheelchairs as mobility assistive equipment are becoming more enriched and extended. Although there is a well-established body of literature on fatigue detection methods and systems, fatigue detection for wheelchair users has still not been widely explored. This paper proposes a neuro-fuzzy fatigue tracking and classification system and applies this method to classify fatigue degree for manual wheelchair users. In the proposed system, physiological and kinetic data are collected, including surface electromyography, electrocardiography, and acceleration signals. The necessary features are then extracted from the signals and integrated with a self-rating method to train the neuro-fuzzy classifier. Four degrees of fatigue status can be distinguished to provide further fatigue and alertness prediction in the event of musculoskeletal disorders caused by underlying fatigue.

INDEX TERMS Fatigue, ECG, EMG, neuro-fuzzy classifier, body sensor network, smart wheelchair.

I. INTRODUCTION

With the continuous growth of the elderly and disabled population worldwide, there is an increasing demand for mobility assistive equipment. The wheelchair is one of the most practical devices and is widely used by elderly and disabled individuals. Since research on the efficient design of wheelchairs has been in the spotlight for over two decades, researchers have focused on a wide variety of fields, including health informatics, assistive robotics, and human-computer interaction [1]. According to the latest report from the World Health Organization [2], more than 1 billion people suffer from different degrees of disability and handicaps around the world. Nearly 20% of this population experience relatively extreme difficulties in their daily lives due to severe physical impairments. However, the existing assistance products on the market are still very far from meeting the practical requirements of such customers. Therefore, enriching and extending the wheelchair with multiple functionalities is becoming an active area of research. Even though wheelchairs are becoming increasingly intelligent and multi-functional with the use of smart sensors and electronic elements, wheelchair users still have some fundamental needs that are worthy of investigation.

It is known that cumulative physical fatigue can easily give rise to musculoskeletal disorders (MSDs) [3] such as spinal cord injury, stroke, or paralysis, especially for athletes who train with high-intensity exercise over long periods every day. Therefore, detecting and monitoring fatigue are very important aspects in preventing the development of such disorders. In recent years, fatigue detection and classification have been widely studied in the sport [4] and automotive domains. In fact, athletes are one of the most vulnerable groups suffering from MSD during dynamic exercise. Similarly, driver fatigue can have disastrous consequences. Researchers have concentrated on the analysis of surface electromyography (sEMG) [5] and heart rate variability (HRV) [6] in combination with multi-sensor fusion techniques in body sensor networks [7], [8] to indicate fatigue states and prevent injuries. However, most of the literature specifically concentrates on changes in the physiological features between non-fatigue and fatigue states [9], and most experiments are implemented in a laboratory setting [10]. In addition, wheelchair users, who represent another community susceptible to MSD, have not been considered in previous research. Mobility-impaired individuals and seniors are usually not as sensitive as healthy adults in perceiving underlying physical fatigue. Thus, based on the above issues, a practical and universal method for the detection and classification of fatigue degree for wheelchair users is significantly meaningful in preventing them from acquiring these irreversible disorders and, ultimately, in improving their quality of life.

This work employs a neuro-fuzzy classification method [11] and a wheelchair system consisting of multiple wearable sensing devices (sEMG, ECG and accelerometer sensors) to classify fatigue degree. In our proposed system, all physiological and kinetic signals are collected in a non-laboratory setting. Furthermore, a neuro-fuzzy classification system is beneficial in describing the uncertainty of the relationship between fatigue and biological signals since the membership function can describe the degree of membership in the corresponding fuzzy set (fatigue set or non-fatigue set) [12]. Our method can effectively categorise fatigue degree and reduce unnecessary feature extraction and execution in the algorithm. Thus, our approach can be applied in real life and can serve as a fatigue indicator with a relatively high accuracy to effectively prevent wheelchair users from developing MSD.

An early prototype of such a wheelchair has been described in [13]. The major contributions of this work are as follows:

- Use of fewer muscles to acquire effective sEMG signals and fewer features to detect and categorise fatigue degree;
- Use of a fuzzy inference system to classify fatigue degree in a non-laboratory setting;
- Development of a fatigue detection and classification wheelchair system targeting a more vulnerable social group (motor-impaired and elderly people).

In this paper, we present a complete wheelchair system with fatigue detection and classification functionalities and discuss the validation of the system, which shows a relatively high degree of accuracy. Section II introduces the related work in terms of the state-of-the-art of smart wheelchair and existing dynamic state fatigue detection methods. Section III details the designed system and the proposed fatigue detection and classification method. In Section IV, we analyse the sEMG signals from different muscles, illustrate the relationships between physiological features and fatigue degree and validate the accuracy of our system. In Section IV-D, some research challenges and potential solutions are discussed. Finally, in Section V, conclusive remarks are drawn.

II. RELATED WORK

A. SMART WHEELCHAIRS

To facilitate the independence of impaired people, many scientific works aiming to make the electric wheelchair "smarter" have been proposed. Such works, summarised in [1], aim to enrich the functionalities of wheelchairs in terms of health informatics, assistive robotics, human-computer interaction and emotion and behaviour recognition.

Health informatics concerns the monitoring of various health parameters, including heartbeat, respiration rate, and blood pressure, and recognizing physical and psychological states to avoid emergencies [14]. Assistive robotics is another important set of technologies that can be used to upgrade the smart wheelchair [15]. Researchers have primarily concentrated on extending the features of the smart wheelchair in terms of navigation, obstacle detection, and safety maintenance, which effectively improve mobility by employing assistive alternatives. Due to the different impairments of wheelchair users, a wide range of human-computer interfaces are available for controlling traditional manual wheelchairs [16]. Facial movement, eye movement, and sEMG signals are used extensively to control electric wheelchairs. Finally, emotion and behaviour recognition [17] are being applied in smart wheelchairs to reduce the burden of caregivers in their care for disabled and elderly people in combination with different communication techniques (e.g., wireless sensor networks, Bluetooth, and Global System for Mobile Communications).

B. FATIGUE DETECTION IN DYNAMIC STATES

Physiological fatigue can be defined as the loss of maximal force-generating capacity during muscular activity or as the failure of the functional organ, while psychological fatigue has been defined as a state of weariness related to reduced motivation [18]. Undoubtedly, people in dynamic states experience these two kinds of fatigue, which often occur simultaneously. The aggregation of underlying fatigue during dynamic states usually causes serious injuries that can be irreversible. Therefore, the best way to avoid such injuries is to detect fatigue, classify its degree and ultimately try to predict it.

Muscle fatigue is one of the most significant sources of human fatigue. Most muscle fatigue detection methods are based on the analysis of sEMG signal parameters. González-Izal et al. [19] comprehensively describe linear and non-linear sEMG models for estimating muscle fatigue. In these models, the amplitude- and spectrum-based parameters' i) averaged rectified value (ARV), ii) root mean square value (RMS), iii) mean power frequency (MPF), and iv) median frequency (MDF) are applied to assess muscle tiredness in daily life [20], [21]. Specifically targeting repetitive upper limb tasks [10] such as wheelchair propulsion, the change in instantaneous mean power frequency (IMPF) is used to indicate and quantify muscle fatigue.

However, since muscle fatigue is just one source of human tiredness, other aspects, such as cardiac activity, are considered to improve the accuracy of human fatigue detection and classification. Eskofier et al. [22] utilises 3 heart rate features, 9 Heart Rate Variability (HRV) features and other biomechanical features to distinguish the runner's fatigue state and achieved an accuracy of 88.3%. In addition, the spectral

TABLE 1. Comparison of related works.

Reference	Sensors or Equipment	Fatigue Indicator	Physiological source	Kinematic source
[9]	SmartWheel, sEMG sensor	MPF, EMG intensity	√	√
[10]	sEMG sensor	MDF, AEMG	√	
[20]	sEMG sensors	ARV	√	
[21]	Accelerometer, sEMG sensor	MPF	√	√
[22]	Magnet, stride sensor	HRV, HR, biomechanical features	√	√
[23]	ECG sensor	HF, LF, LF/HF	√	
[27]	Accelerometer	Acceleration		√

analysis of HRV has been used as an indicator to assess driver fatigue [23]. According to these studies, fatigue can lead to variability in ECG signal parameters. Total power (TF), low-frequency power (LF), high-frequency power (HF) and low-/high-frequency power (LF/HF) are widely analysed in the frequency domain as basic indexes of fatigue, and the mean heart rate value (HRmean) and standard deviation of beat-to-beat intervals (SDNN) are examined in the time domain [24]. Yanci et al. compare the differences in the heart rate peak and HRmean between fatigue and non-fatigue states for wheelchair basketball players [25]. Although physiological signals such as ECG and EMG can be effectively used in the analysis of human fatigue, kinematics information cannot be ignored. Fatigue detection for wheelchair users is an emerging direction in research [26]. Accelerometers have been attached to wheelchairs to analyse fatigue in users with lower limb paralysis [27]. Patrick et al. combine myoelectric signals with pushrim data from the SmartWheel recording system to acquire both physiological and kinematic data to assess the time remaining until muscle fatigue [28]. A comparison of the related works is reported in Table 1.

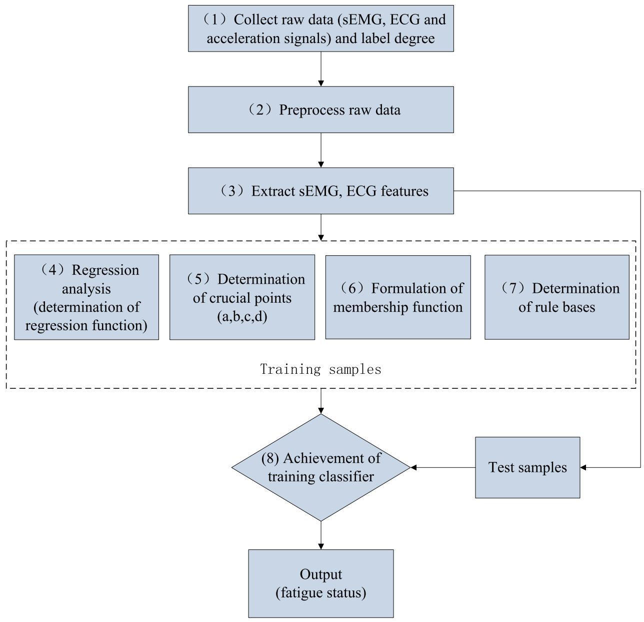

FIGURE 1. Flowchart of the proposed method based on a neuro-fuzzy classifier for fatigue classification.

III. FATIGUE CLASSIFICATION METHOD

In Figure 1, the proposed fatigue detection and classification method based on a neuro-fuzzy classifier is depicted. During the experiments, we collected all raw physiological and kinetic data as well as information labeled by the subjects, and preprocessing and signal feature extraction are then implemented (see Section III-C). The features extracted from the training samples represented the input for training the neuro-fuzzy classifier. Specifically, we conducted a regression analysis on the feature data to identify the crucial variables and formulate the membership function. After that, the rule base was further determined according to the training sample data integrated with the self-reported fatigue data reported by the subjects. Section III-D provides details on the neuro-fuzzy classifier. Finally, we imported testing data into the neuro-fuzzy classifier and matched the outputs with real fatigue degrees reported by subjects to calculate the accuracy of our system.

A. SYSTEM ARCHITECTURE

The smart wheelchair-based fatigue measurement system (described in detail in our previous work [13]) is depicted in Figure 2. The fatigue-tracking system is composed of a smart wheelchair layer, a smartphone layer and a data analysis layer. Signals are transfered among those layers via Bluetooth. Regarding hardware, the smart wheelchair layer involves a Shimmer sEMG sensor, an ECG-enabled Shimmer sensor and one accelerometer, which are used to acquire both physiological and kinetic signals. The smartphone layer is based on a smartphone with a custom application for playing audio fatigue questions and the Runtastic App to check real-time speed and elapsed time in the experiment phase. Finally, all collected signals are transmitted via Bluetooth to the data analysis layer, which includes a central processing computer with a well-trained neuro-fuzzy classifier (see Section III-D) to recognise fatigue degree. This data analysis layer is also in charge of managing the entire Body Sensor Network (BSN) [29]. Moreover, when the fatigue degree is detected and classified in the real scenario, the classified fatigue degree is delivered via Bluetooth from the data analysis layer to the smartphone, which presents the fatigue degree to the wheelchair user.

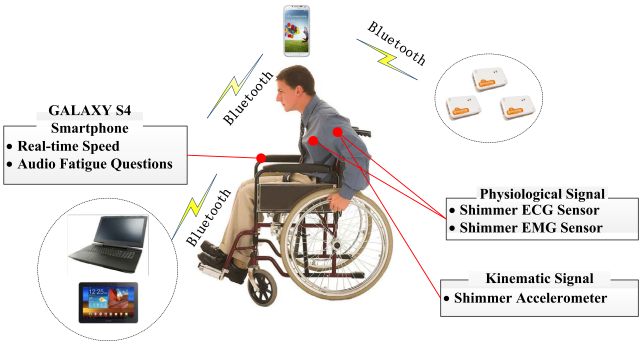

FIGURE 2. Diagram of hardware deployment and communication between layers.

B. EXPERIMENTAL SETTING

In our experiments, we recruited eight volunteers (5 males, 3 females, mean age 25±5years, mean weight 60±15kg) i) without any history of upper-limb injury or neuromuscular disorder to execute the designed exercise and ii) without medical contraindications, such as severe concomitant disease, alcoholism, drug abuse, or psychological problems. Each subject performed 8 trials on a flat paved surface, of which 7 trials were used for training while 1 trial was utilised for testing. Figure 1-(1) depicts the data collection procedure; during each trial, the sEMG and ECG data are collected and labeled with the fatigue degree level reported by the participant.

Before initiating the experiment, the subjects were informed of the purpose and procedures of the experiment and were then asked to follow the experimental protocol detailed below. Specifically, the subjects were asked to attach the sEMG electrodes on the belly of the middle deltoid and ECG electrodes to the left of the sternum in the fourth intercostal space. These areas must be shaved and then cleaned with 90% alcohol. The electrode wires were then secured to the muscle using double-sided adhesive tape. The participants were required to propel the wheelchair and maintain a constant speed of 1.6 m/s [9](a rather fast speed so as to accelerate the development of fatigue) on a flat concrete track until they were not able to maintain the target speed. The speed was easily checked by the Runtastic App on the smartphone, which also played the audio fatigue questions during the trial. The sEMG, ECG and acceleration signals were acquired with the Shimmer units and transferred to the central processing PC via Bluetooth. At the same time, participants used the self-ratings described in Table 2 to label their fatigue degree during each trial [30].

The experimental protocol is described in the following:

- Step 1: We choose a 10-meter-long track to allow the subjects get used to the track and achieve the required speed of 1.6 m/s during the preparatory phase.
- Step 2: Subjects must maintain 1.6m/s on a 500-meter track until they are not able to maintain the speed.
- Step 3: Participants label their fatigue according to the four degrees in Table 2 during Step 2. Subjects must verbally report their fatigue degree level, as in Table 2, throughout the experiment. At the same time, the experimental observer uses MultiShimmerSync to annotate the data according to the subject's labeling.
- Step 4: Each subject repeats the previous steps twice per day (morning and afternoon). In total, we spent 4 days collecting the data obtained across 8 sessions from each participant.

TABLE 2. Self-rating description.

Spoken Answer	Meaning	Status
0	Not at all	Non-fatigue
1	Little	Transition
2	Rather	Transition
3	Extremely	Fatigue

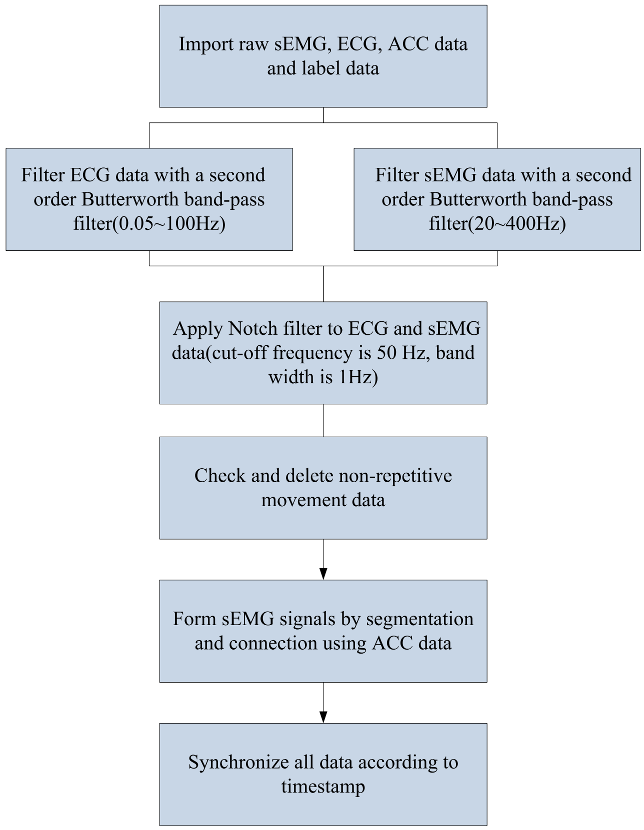

FIGURE 3. Preprocessing flowchart.

C. SIGNAL PREPROCESSING AND FEATURE EXTRACTION

1) PREPROCESSING OF sEMG, ECG AND ACCELERATION SIGNALS

In Figure 1-(2), we preprocess the sEMG and ECG data using multiple filters and segment those data by acceleration signals. Figure 3 shows the preprocessing flowchart. The first filtering phase removes the baseline and movement artifact noise from the sEMG, ECG and acceleration

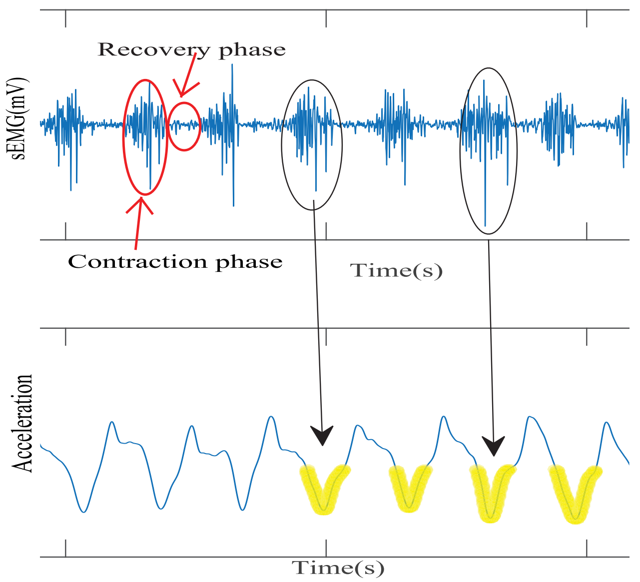

FIGURE 4. **Diagram of the segmentation and connection of sEMG signals.**

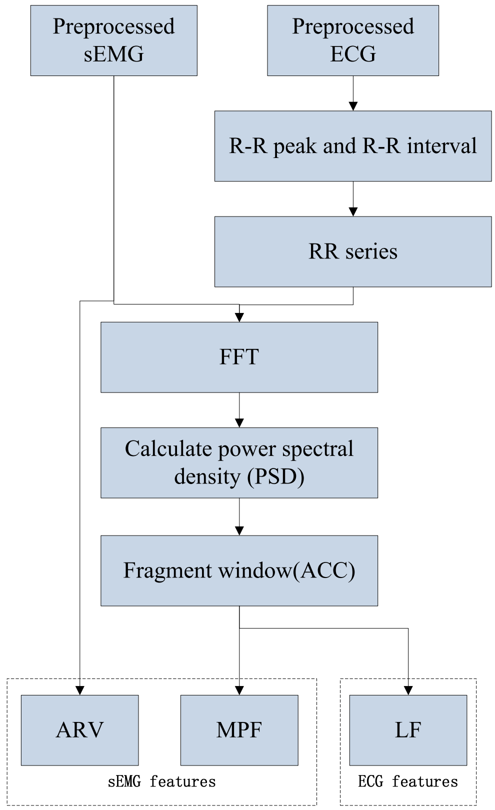

FIGURE 5. **Diagram of feature extraction.**

signals [31], [32]. The sEMG and acceleration signals are sampled at 512 Hz [33]. Although it is often recommended to sample sEMG at 1024 Hz, we chose 512 Hz to reduce packet loss. The ECG signal is sampled at 102.4 Hz according to previous results [34], in which Shimmer 2R sensors were used for the same purpose as in this study and in which the ECG signal was sampled at 100 Hz. We then applied a second-order Butterworth band-pass filter (20 400 Hz) to the sEMG signals and a band-pass filter (0.05 100 Hz) to the ECG signals [13] in the time domain because these two frequency bandwidths include the most efficient sEMG and ECG signals. Then, a notch filter with a 50 Hz cut-off frequency and 1 Hz bandwidth is used to remove power line interference. All non-repetitive data, including the sEMG, ECG, acceleration and label signals, that correspond to the very first and final data of the trial should be eliminated because the wheelchair users are not executing periodic movements. Then, because wheelchair propulsion is a repetitive movement and because each propulsion consists of a contraction and a recovery phase corresponding with active sEMG and inactive sEMG signals, respectively, we segment the contraction movement and connect the corresponding active sEMG signals using the acceleration data, which is useful in recognizing arm movement [35]. The contraction and recovery phases are shown in Figure 4. Finally, the preprocessed data are synchronised using the timestamp.

2) EXTRACTION OF FEATURES STRONGLY RELATED TO FATIGUE

The sEMG and ECG signal features that are strongly associated with fatigue are widely described in the literature [19], [24]. EMG features such as MPF, ARV, and MDF are often used as fatigue indexes, while HRV features such as LF, HF, and SDNN are often used to indicate fatigue status. As described in Figure 1-(3), we select the MPF and ARV of sEMG signals and the LF of ECG signals as the input sources for classifying fatigue degree. The chosen features are the most widely used according to the literature (see Section II-B). Our preliminary experiments show clear relationships between these features and fatigue degree (see Section IV-B). The feature extraction procedure is described in Figure 5. The ECG features, RR peak and RR interval [36] can be extracted using the Kubios software [37]; Fast Fourier Transforms (FFT) are then applied to RR series, thus obtaining the power spectral density (PSD). FFT and PSD are also applied to the preprocessed sEMG signal. Furthermore, the LF, MPF and ARV are calculated using the fragment window scaled by the acceleration signal in Figure 4. The computation formulas are presented below:

$$ARV = 1/n \sum_{i=1}^{n} x_n \tag{1}$$

where x_n is the value of the sEMG signal and n is the number of sample.

$$MPF = \frac{\int_{u_1}^{u_2} u \cdot PSD(u)\, du}{\int_{u_1}^{u_2} PSD(u)\, du} \tag{2}$$

MPF denotes the mean power frequency at time t, which is the middle time in every fragment time window, while $PSD(u)$ is the power spectrum density at frequency u. u_1 and u_2 are calculated as the smallest and largest frequencies, respectively, after applying FFT to the sEMG signal in every fragment time window.

$$LF = \int_{f_1}^{f_2} PSD(f)\, df \tag{3}$$

Additionally, the definition of the LF of the ECG is the area under the PSD function, with the frequency ranging from 0.04-0.15 Hz. Therefore, f_2 is equal to 0.15 Hz, while f_1 is equal to 0.04 Hz.

D. FATIGUE CLASSIFICATION BASED ON NEFCLASS

The first neuro-fuzzy approach (NEFCLASS) for data classification was proposed by Nauck and Kruse [38]. Fuzzy logic, as an important concept in fuzzy inference systems (FIS), can integrate human decision-making in the form of IF-THEN rules. Since the relationship between the sEMG, ECG, acceleration signal features and fatigue cannot be quantified directly, the fuzzy set, which is used to represent some form of uncertainty, can describe it effectively. All of the relationships between the feature inputs and fatigue (or non-fatigue) can be fuzzed into values of [0, 1], which is expressed by the membership function. Then, the integration of the IF-THEN rules and the fuzzy sets determines the output. All membership functions and the IF-THEN rules should be trained and defined using large datasets and acquired knowledge.

The adaptive neuro-fuzzy inference system for classification has been implemented in MATLAB with our custom code and fuzzy logic toolbox [39].

In our work, we adopted the Mamdani system as our FIS [40]. Although Mamdani-type fuzzy inference is similar to the method proposed by Sugeno [41] in many aspects, the former is more suitable for human input and the expression of human knowledge. As depicted in Figure 1-(6), an S-shaped membership function was used to express the fuzzed input, in which we use the slope of MPF, ARV and LF as input variables due to their conformities to the function shape. Figure 6 presents the FIS structure with 3 inputs, denoted by I_i, the 8 rule bases in Table 3, as determined by the training data (subjective, physiological and kinematic data) and experimental experience as well as the 3 Z_i outputs.

TABLE 3. Rule bases integrated with self-rated fatigue degrees.

Rule	Input			Output
0	I1	I2	I3	Self-rating
1	high	high	high	Extremely
2	high	high	low	Rather
3	high	low	high	Rather
4	low	high	high	Rather
5	high	low	low	Rather
6	low	high	low	Rather
7	low	low	high	Rather
8	low	low	low	Not at all or little

As shown in Figure 1-(4), after feature extraction, we calculated the slope of each feature and analysed it by

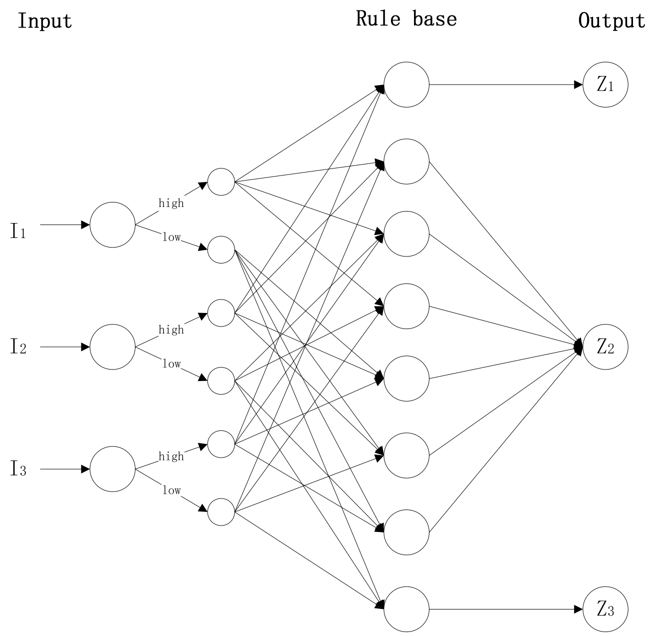

FIGURE 6. Structure of a neuro-fuzzy network for classification.

curve fitting. $f(t) = aln(t)+b$ was the selected curve function for all features; this function has been validated as the most proper fitting curve for sEMG signals [10]. We also compared another normal fitting curve and found it to be meaningful for ECG signals. Furthermore, as shown in Figure 1-(7), the crucial membership parameters and rule bases are determined by a large amount of data (see Figure 1-(5)). Finally, we imported the test sample into the trained classifier.

IV. STUDY RESULTS

A. ANALYSIS OF THE sEMG SIGNALS OF DIFFERENT MUSCLES

In a laboratory environment, a large number of muscles should be considered in fatigue measurement [42] to guarantee recognition accuracy. However, too many sensors, electrodes and wires attached to the human body will affect the comfort of the subject. Especially during a dynamic activity, the use of several devices obstructs natural movement. A trade-off between accuracy and wearability is a critical research issue. Therefore, we analysed the performances of different specific muscles proposed in the literature during normal wheelchair propulsion exercises and chose the muscle with best performance as the target for collecting the sEMG signal. Figure 7 shows the sEMG signals of seven distinct muscles in the upper limbs; it is evident that the middle deltoid has the most distinctive boundary between the contraction and recovery phases. Moreover, the statistical parameters (i.e., Standard Deviation (SD) and Mean Value (MV)) demonstrated in Table 4 support this choice. Our analysed statistical parameters focus on the contraction, recovery, and whole propulsion phases. We collected 60-s sEMG signal segments in the propulsion trial with a fixed speed of 1.6 m/s.

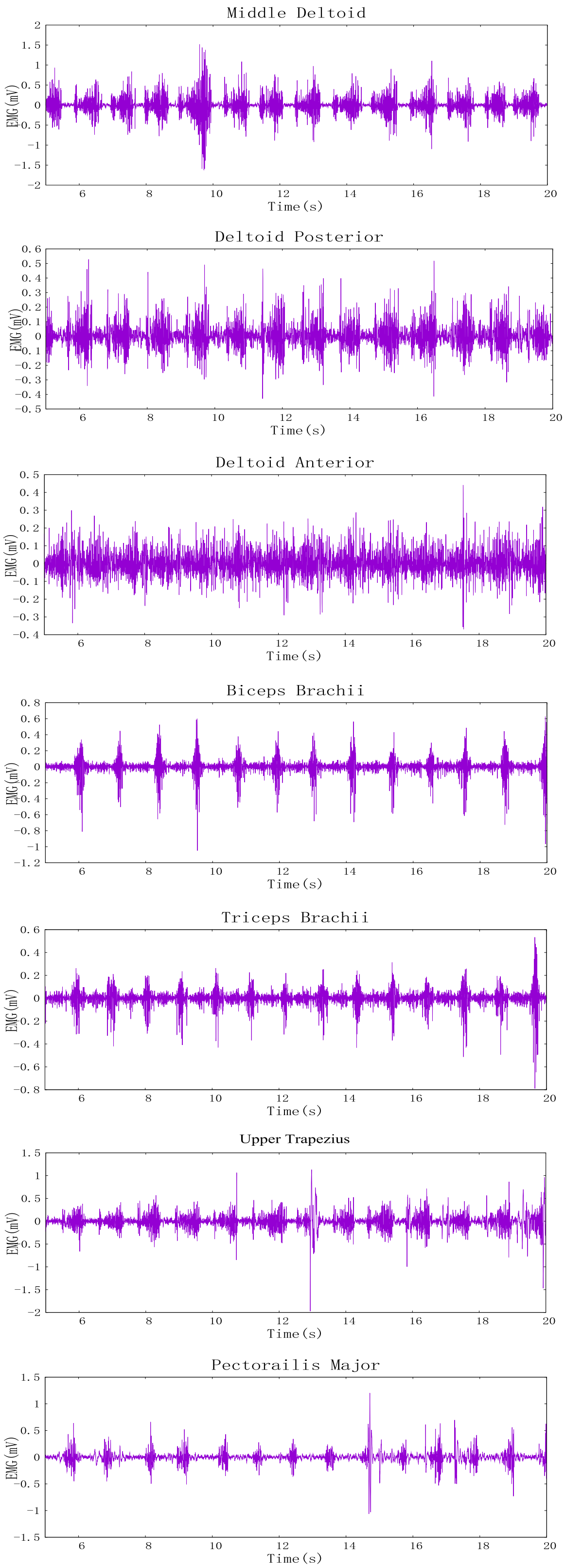

FIGURE 7. Comparison of the sEMG signals of 7 different muscles.

During the recovery phase, the SD was calculated and formed into a sequence that we call the standard deviation series of recovery (SDSR). The same parameter was calculated in the contraction phase (the standard deviation series of contraction (SDSC)). Then, the MVs of the SDSR and SDSC were calculated. In addition, we used the SDSR and SDSC to obtain a new series according to the time sequence called the standard deviation series of propulsion (SDSP). Then, the SD of SDSP was calculated.

The SDSR shows the stability of the recovery phase because the muscle is not active and the signal should have a tiny fluctuation that can be revealed with a small SDSR value. In contrast, the SDSC should have a relatively greater value, which means that the sEMG signal of the contraction phase fluctuates considerably when this muscle shows a more active status. We calculate the MV of the SDSR and SDSC to acquire this information from the whole trial. The SD of the SDSP represents the distinction between the contraction and recovery phases. The fluctuation in the SDSP, which corresponds to the SD of the SDSP, helps better understand the information from the whole trial. When the SDSP fluctuates more noticeably, the boundary between the contraction and recovery phases is more clear. In other words, the larger the value of the SD of the SDSP, the more distinct the difference is between the contraction and recovery phases.

According to the data in Table 4, it is clear that the middle deltoid has the lowest SDSR value and the highest SDSC value. This means that the sEMG signal from the middle deltoid has a stable recovery phase and a fluctuating contraction phase. At the same time, although the SD of the SDSP in middle deltoid signal is not the highest compared to the other muscles, it still has a rather large value, demonstrating the clarity of the sEMG signal. To summarise, there are three reasons for choosing the middle deltoid as the target muscle. First, the recovery phase sEMG signals change slightly. Second, the large fluctuation in the contraction phase sEMG signals demonstrates their activity. Third, the sEMG signals for the whole trial show a clear boundary between the contraction and recovery phases.

B. THE TRENDS OF FEATURES DURING WHEELCHAIR PROPULSION

To avoid physiological similarity within the set of participants, we the analysed ECG and EMG data of all the subjects to validate the homogeneous tendency of the relationships between physiological features and fatigue status. Here, we utilise the trial data extracted from four subjects from our database to demonstrate this tendency and validate the homogeneity. Following our experimental protocol, after we collected the data, we selected one trial from the 4 different participant trial sets and calculated the features of the sEMG and ECG signals (i.e., MPF, ARV, and LF). Then, by using regression analysis, we discovered that these features have the same trends during each experimental trial between different subjects. More precisely, the MPF trend for different subjects is homogeneous, experiencing an evident decrease. As shown in Figure 8, the trends of the 4 subjects exhibit the same behavior: the MPF decreases with increasing tiredness. This relationship between muscle

TABLE 4. Comparison of time series statistical parameters in the contraction and recovery phases of the sEMG signals.

Muscle type	Mean Value SDSR	Mean Value SDSC	Standard Deviation SDSP
Middle deltoid	0.0397	0.1955	0.0627
Deltoid posterior	0.0492	0.1017	0.0342
Deltoid anterior	0.0828	0.0672	0.0182
Biceps brachii	0.058	0.060	0.0017
Upper trapezius	0.1012	0.0448	0.0410
Pectoralis major	0.1281	0.1680	0.0811
Triceps brachii	0.1331	0.0757	0.0719

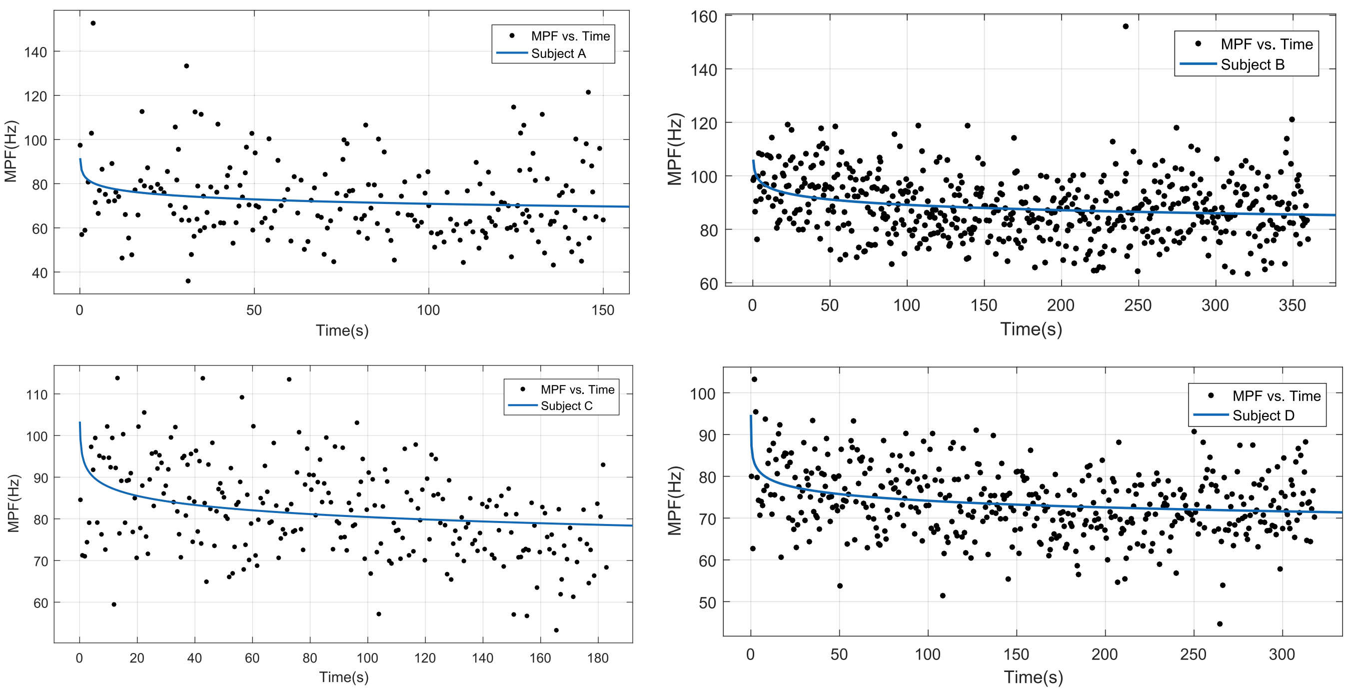

FIGURE 8. The relationship between MPF and fatigue during each trial for 4 different subjects.

fatigue and the MPF of the sEMG signal is consistent both with the conclusion of Merlettia [43] and with the experiment performed by Roman-Liu et al. [10]. Although our curves are not as clean as those of Roman-Liu et al. (it is worth noting that their experiments were performed in a strictly controlled laboratory environment), they still convincingly demonstrate the similarity in the behaviour in our practical environment. Moreover, we illustrate changes in the other two physiological parameters associated with fatigue degree. With increases in the fatigue of a wheelchair user, the ARV of the sEMG shows an increase, as demonstrated in Figure 9, whereas the LF of ECG decreases considerably, as seen in Figure 10.

C. CLASSIFICATION ACCURACY

According to our literature analysis, there is little research on the classification of fatigue, and most studies have examined the accuracy of fatigue detection. For example, Patel et al. use HRV as the human physiological measure to detect the early onset of fatigue in drivers [23]. Although a high accuracy of up to 90% has been achieved in detecting human fatigue, the classification of multiple degrees of fatigue can definitely be improved [22]. The three different fatigue degrees proposed in our work make sense in terms of the prediction and identification of fatigue. More precisely, the "rather" status could be used as an indicator of pre-fatigue, thus reminding the wheelchair user to avoid cumulative underlying fatigue. In Table 5, we compared the classification accuracy of our proposed method and the results obtained by Eskofier et al. [22]. In [22], the classification rates of two different classifiers (Support Vector Machine [44] (SVM, linear kernel) and Linear Discriminant Analysis [45] (LDA)), were compared. Distinct physiological and kinematic features and feature numbers were chosen for the comparison of

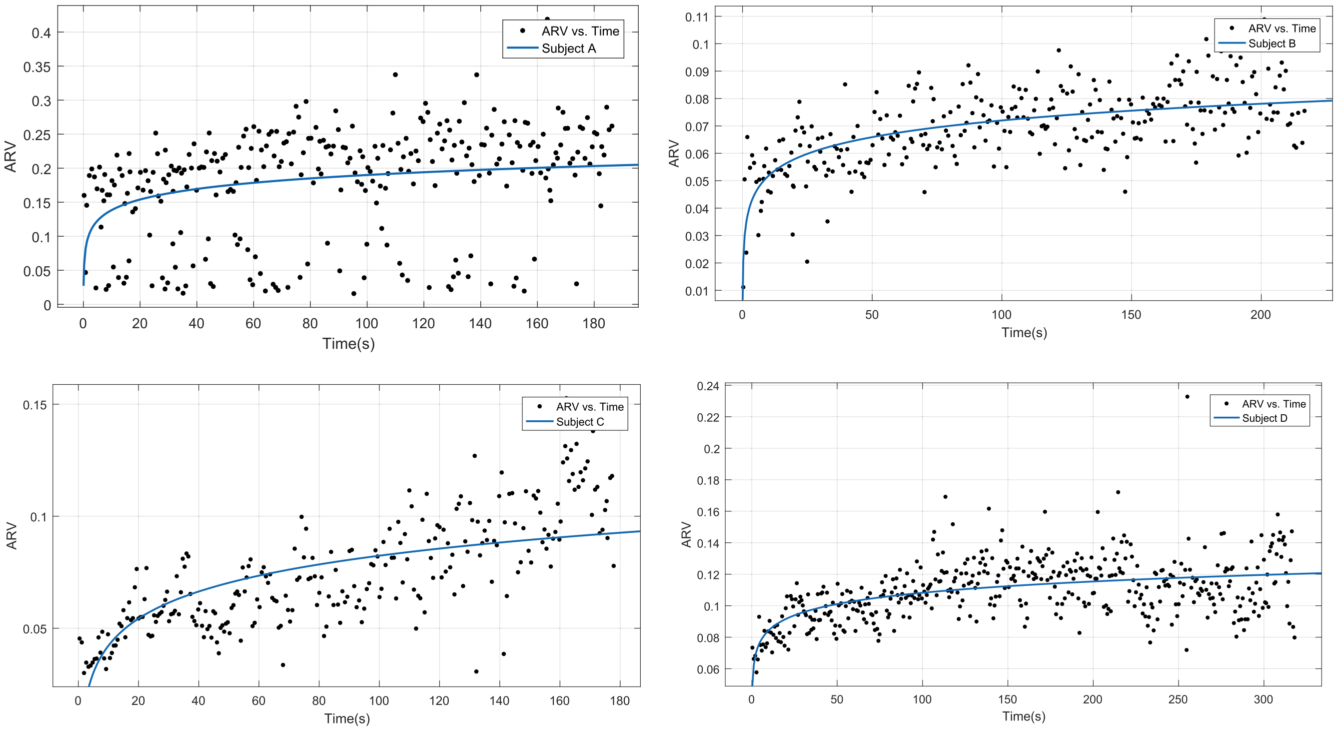

FIGURE 9. The relationship between ARV and fatigue during each trial for 4 different subjects.

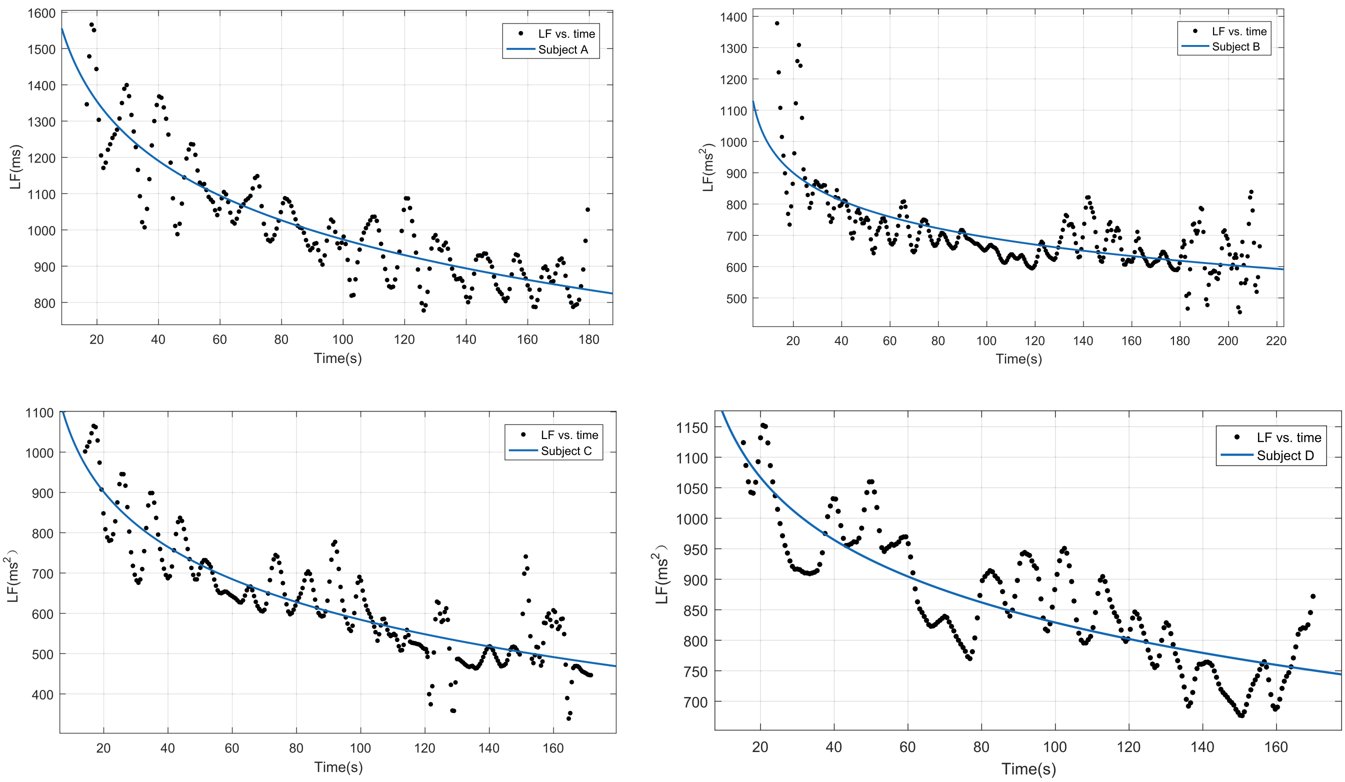

FIGURE 10. The relationship between LF and fatigue during each trial for 4 different subjects.

classification results. From this comparison, we can observe that combining physiological and kinematic features leads to better performance than a single feature source when detecting fatigue degree. Eskofier can use two feature types to reach 89.8% accuracy, which is higher than either the single kinematic feature accuracy of 88.2% or the single

TABLE 5. Comparison of the accuracy of different features and classification algorithms.

Feature number	Feature type	Eskofier's method SVM	Eskofier's method LDA	Our proposed method NF
1	Physiological	61.7%	62.4%	-
2	Physiological	68.5%	68.0%	78%
3	Kinematical and physiological	-	-	80%
19	Kinematical	88.2%	87.3%	-
22	Kinematical and physiological	89.8%	88.3%	-

physiological feature accuracy of 68.5%. Our analysis also illustrates the same behaviour, in which the accuracy is improved to 80% by integrating kinematic information. In fact, without the kinematic information from the accelerometer to segment the sEMG signals, the relationship between sEMG features and fatigue cannot be demonstrated very clearly in a practical environment. Therefore, we can conclude that it is better to include a greater variety of data sources to recognise fatigue. Secondly, our proposed method used fewer features to achieve a relatively high accuracy of up to 80%. Even though Eskofier achieved up to 89.8% accuracy, many more features are needed and fewer fatigue degrees were distinguished. In other words, our proposed method can distinguish three fatigue levels (non-fatigue, rather and fatigue), while Eskofier's method only proposed two fatigue levels (low perceived fatigue and high perceived fatigue). Finally, the neuro-fuzzy classifier outperforms the other two classifiers (SVM and LDA) in analyzing physiological signals. Specifically, we can reach a 78% accuracy by analyzing two sEMG features, while an approximately 68% accuracy was achieved using Eskofier's method. Therefore, the neuro-fuzzy classifier demonstrates an advantage in terms of the classification of physiological signals.

D. DISCUSSION

The accuracy of our neuro-fuzzy network can be improved in different ways. In this research, the neuro-fuzzy network, when applied to sEMG, ECG, and acceleration signal features, achieved an accuracy of 80%. As these physiological and kinematic signals vary with different individuals, data from more subjects with different physiologies should be collected and used to train the neuro-fuzzy network. This will provide the network with sufficient learning on the different variations in these features and would thus further increase the accuracy of the network. Membership function also plays an important role in improving the accuracy of the neuro-fuzzy network since a more precise representation of the probability of fatigue degree would result in a higher accuracy. The rule base is also of great importance: the discovery of a more reasonable rule base would be a good way to further increase the accuracy.

In addition to sEMG and ECG signals, electroencephalogram (EEG) [46] signals are a significant source of fatigue features and have been previously analysed to recognise human fatigue by attaching the electrodes to the scalp. In future work, we aim to improve the accuracy of this method by selecting and adding other effective features from the EEG signal. To improve our dataset and more deeply analyse the accuracy of our method, we will continue our experiments to collect more sEMG, ECG and acceleration data and to introduce EEG information.

V. CONCLUSIONS

This paper proposed a complete fatigue-tracking and fatigue-classification method and system for wheelchair users. For classification, the fatigue degrees were derived from sEMG and ECG features and integrated with acceleration signals of propulsion movements. The raw signals were preprocessed to remove baseline and movement artifacts to improve the signal-to-noise ratio (SNR). From the preprocessed signals, the extracted features (MPF, ARV and LF) have been demonstrated to be strongly associated with human fatigue. The relationship between these features and the fatigue degree was demonstrated with regression analysis. Furthermore, by applying our experimental protocol, we created a dataset to train a novel neuro-fuzzy classifier and achieved a relatively high classification accuracy of 80%, obtained by distinguishing between three fatigue levels (''non-fatigue,'' ''rather,'' and ''fatigue''). Additionally, we analysed the sEMG signals of seven muscles and selected the middle deltoid as the target muscle because its EMG signal provides clear indications of fatigue during wheelchair propulsion. This allowed us to reduce the number of required sensors and thus improve system wearability.

The contributions of our work have been described in many aspects. We targeted the most vulnerable groups in society - the disabled and the elderly - to improve their quality of life. Our experimental setting was a non-laboratory environment, which is more beneficial for the practical application of our method. Regarding hardware, we minimised the number of sensors. In the future, a close-fitting vest with a small number of embroidered electrodes could be designed to further improve the wearability of the system. Furthermore, we extracted fewer features, reducing the computation load and speeding up the execution of the embedded implementations.

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WENFENG LI (SM'11) received the Ph.D. degree from Wuhan University of Technology, Wuhan, China, in 2000. He was with the Royal Institute of Technology, Sweden, as a Visiting Scholar in 2003. He was a Visiting Professor with the New Jersey Institute of Technology in 2012 and with CUSP, New York University, in 2015. He set up the Institute of Logistics and Robotics, the Center of Internet of Things (IoT) and Logistics Technologies, and the International Joint Lab of IoT. He is currently a Professor with the School of Logistics Engineering, Wuhan University of Technology. He and his research group have conducted over 20 scientific research projects, with funding from the National Natural Science Foundation of China, the MOST Research and Development Project, and the research and development projects of different provinces in China. He holds over ten patents and has authored or coauthored over 150 academic papers and four academic books. He has co-edited several international conference proceedings and two international special issues: Collaborative Wireless Sensor Networks in a special issue of the *International Journal of Information Fusion* (Elsevier), in 2015 and Enhancing Internet and Distributed Computing Systems with Wireless Sensor Networks in a special issue of the *International Journal of Distributed Sensor Networks* in 2015. His current research interests include swarm intelligence, the IoT and robotics, and the modeling and simulation of logistics systems.

XINYUN HU received the M.S. degree from the School of Logistics Engineering, Wuhan University of Technology. She is currently pursuing the Ph.D. degree at the School of Aviation, University of New South Wales. Her master's thesis was related to the Smart Wheelchair Program at the Robotics and Logistics Laboratory, Wuhan University of Technology, and the SenSysCal Laboratory, Univesity of Calabria, and the assessment of physiological and psychological fatigue for wheelchair users. She spent one year as a Researcher with the University of Calabira, Rende, Italy. She has authored or coauthored two conference papers, and holds two patents related to WSNs, intelligent robotics, and Internet of Things. During her studies, she was involved in fatigue detection and classification from both physiological and kinematic points of view.

RAFFAELE GRAVINA received the Ph.D. degree in computer engineering from the University of Calabria, Rende, Italy, in 2012. He spent two years as a Researcher with the Telecom Italia WSN Lab, Berkeley, CA, USA. He is currently serving as a Post-Doctoral Research Fellow in computer engineering with the University of Calabria. He is also the main designer of the SPINE Framework and is responsible for open-source contributions. He is involved in several research projects on WSNs, including BodyCloud and CONET FP7. He is a Co-Founder of SenSysCal S.r.l. He has authored over 50 papers published in international journals, conference proceedings, and books. His research interests are focused on high-level programming methodologies and frameworks for WBSNs, collaborative body sensor networks (BSNs), BSN-cloud computing integration, pattern recognition on physiological signals, human activity recognition and motor rehabilitation assistance, and ECG analysis for cardiac monitoring and emotion detection.

GIANCARLO FORTINO (SM'12) received the Laurea and Ph.D. degrees in computer engineering from the University of Calabria (Unical), Rende, Italy. He holds the Italian Scientific National Habilitation for Full Professorship. He was also a Visiting Researcher and a Professor with the International Computer Science Institute, Berkeley, CA, USA, and the Queensland University of Technology, Australia, respectively. He is currently a Professor of computer engineering with the Department of Informatics, Modeling, Electronics and Systems, Unical. He is also the High-end Foreign Expert of China, an Adjunct Professor with the Wuhan University of Technology, China, and a Senior Research Fellow with the Italian National Research Council—ICAR Institute. He is also the Deputy Coordinator and the STPM of the EU-funded H2020 INTER-IoT Project. He has authored over 300 publications in journals, conference proceedings, and books. His main research interests include agent-based computing, body area networks, wireless sensor networks, pervasive and cloud computing, multimedia networks, and Internet of Things technology. He has participated in many local, national, and international research projects. He was a recipient of the 2014 Andrew P. Sage SMC Transactions Paper Award. He has chaired over 70 international conferences/workshops as co-chair, organized over 25 special issues in well-known ISI-impacted international journals, and participated in the Technical Program Committees of over 350 conferences. He is a Co-Founder and the CEO of SenSysCal S.r.l., a spin-off of Unical, developing innovative IoT-based systems for e-health and domotics. He is the Chair of the IEEE SMC Italian Chapter and the founding Chair of the IEEE SMC Technical Committee on Interactive and Wearable Computing and Devices. He is the founding Editor of the Springer Book Series on *Internet of Things: Technology, Communications and Computing*, and currently serves (as an Associate Editor) on the Editorial Board of the IEEE Transactions on Affective Computing, IEEE Transactions on Human-Machine Systems, IEEE Sensors Journal, IEEE Access, *Journal of Networks and Computer Applications*, *Engineering Applications of Artificial Intelligence*, and *Information Fusion*.