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Robust EMG pattern recognition to muscular fatigue effect for powered wheelchair control

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Abstract. The main goal of this paper is to design an electromyogram (EMG) pattern classifier which is robust against muscular fatigue effects for powered wheelchair control. When a user operates a powered wheelchair using EMG-based interface for a long time, muscular fatigue often arises from sustained duration of muscle contraction. The recognition rate thus is degraded and controlling wheelchair gets more difficult. In this paper, an important observation is addressed that the variations of feature values due to the effect of the muscular fatigue are consistent for sustained duration. Based on this observation, we design a robust pattern classifier through the adaptation process of hyperboxes of Fuzzy Min-Max Neural Network. We present, as a result, a significantly improved performance in terms of the continuous usage of wheelchair.

1. Introduction

As the number of the older persons is rapidly increasing along with the number of the handicapped caused by a variety of accidents, the social demand for welfare and support of state-of-the-art technology are also increasing to lead more safe and comfortable life. In particular, since the elderly or the handicapped have serious problems in doing certain works with their own efforts in daily life, some assistive devices or systems might be very helpful to assist such people or to do the work instead of human beings endowing as much independence as possible so as to improve their quality of life. There are a variety of devices to assist their ordinary activities.

Among them, a powered wheelchair is the most widely used and is known as an effective vehicle to move around the ordinary areas. Conventional powered wheelchairs with the joysticks, however, have limitations for use due to the variety of disability levels of the handicapped and the elderly. Thus various alternatives for controlling the powered wheelchair have been developed such as a sip and puff, chin controller, ultrasonic non-contact head controller, head movement, and voice. In order to maximize the usability, these devices should be carefully designed in consideration of the disability level as constraints.

It is noted that an electromyogram (EMG)-based interface is barely affected by the disability level, because EMG can be acquired from any available muscle. Another advantage of EMG-based interface is the ease-of-use. An EMG-based control can be implemented in an intuitive manner since it reflects human intention on movement.

There is a significant weakness in EMG-based interface, however, which is time-varying characteristic of EMG signals mainly from muscular fatigue effect. For example, when a user operates a powered wheelchair by EMG, the user has to sustain a muscle contraction to control both direction and speed of the powered wheelchair. If the muscle contraction is sustained, muscular fatigue is occurred by the contraction time and system performance is degraded by this fatigue effect.

The main goal of this study is to design an EMG pattern classifier which is robust against muscular fa-

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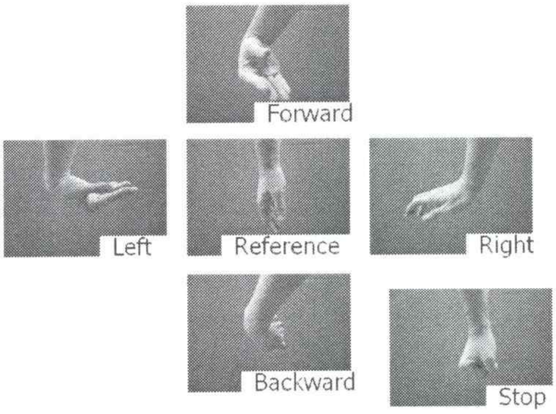


Fig. 1. 6 Basic motions for human-machine interaction

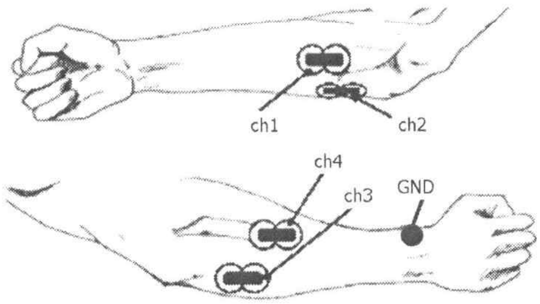


Fig. 2. Placement of surface electrodes for EMG acquisition

tigue effects for powered wheelchair control. For this purpose, the problem of muscular fatigue effect arising from the continuous control action is addressed, and the previous works about muscular fatigue effects and the problems are introduced in Section 2. The proposed approach to solve muscular fatigue effects are presented in section 3. Finally, experimental results are shown in Section 4.

2. Muscular fatigue effect in EMG pattern classification for powered wheelchair control

It is generally desired that more than two wrist movements are dealt with together for EMG-based powered wheelchair control. The minimum degree-of-freedom in the powered wheelchair control is required more than five; up, down, left, right, and click or stop (see Fig. 1). And these actions should be taken constantly as long as the user wants to move the wheelchair. Therefore, muscular fatigue often arises from sustained duration of muscle contraction. Worse, the fatigue levels are also different from each motion even in a same muscle [7]. After all, a muscular fatigue effect should be carefully examined in terms of EMG-based pattern classification. Also, a new fatigue compensation method is desired to meet together with fatigue effects of various motions from human's intention.

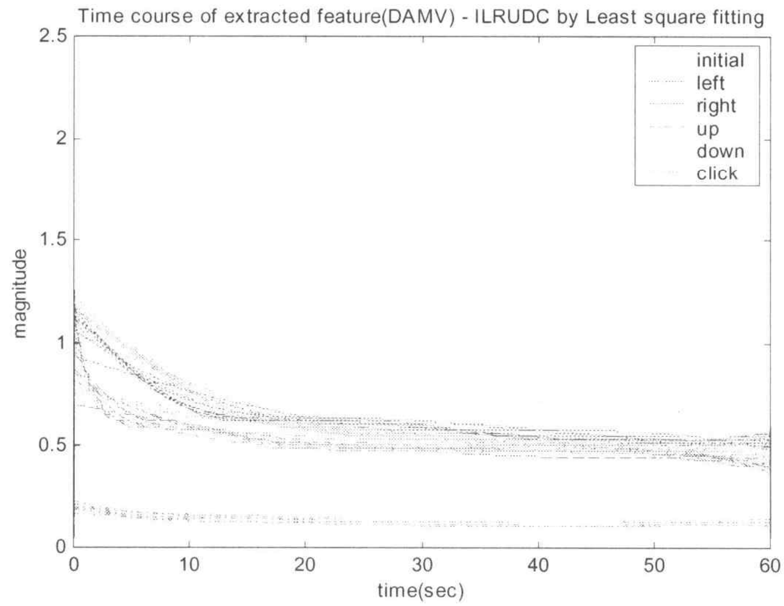
According to a dictionary, fatigue is defined by a feeling of extreme physical or mental tiredness [1]. Muscular fatigue is, therefore, the one due to sustained muscular contraction. Since a muscle movement accompanies with a variety of neural transmissions, muscular fatigue is expressed by complicated procedures. Muscular fatigue is known to be divided by central fatigue and peripheral fatigue according to sustained time of muscle contraction [2]. Central fatigue is defined as fatigue of neural transmission, such as a decrease of the motor unit (MU) firing rate [2]. Peripheral fatigue is defined as fatigue related to biochemical metabolism, such as an accumulation of metabolic by-products in the active muscles and a deficiency of energy sources [2]. Central fatigue is appeared through a couple of hours and a few days. Besides, peripheral fatigue is appeared through only a few second and a few minute [3]. Therefore, peripheral fatigue is more important factor for Human-Machine Interface (HMI) since assistive devices are used occasionally in daily life. We focus on the peripheral fatigue in this study.

Muscular fatigue including peripheral fatigue can be expressed by the relations of characteristic frequencies such as median frequency (MDF) and mean frequency (MNF) [4]. Both MDF and MNF are defined by the following mathematical Eqs (1) and (2), respectively. Here, $P(\omega)$ represents the power spectrum at the specific frequency.

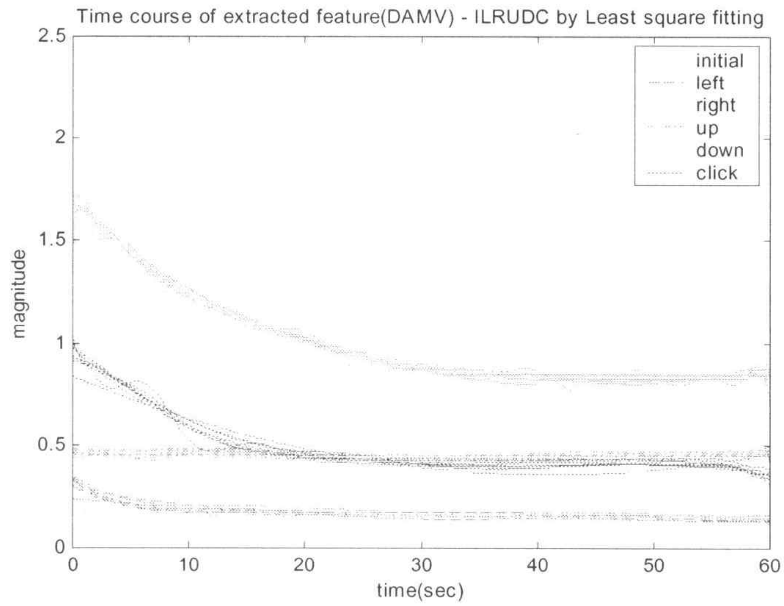
$$\int_0^{MDF} P(\omega)d\omega = \int_{MDF}^{\infty} P(\omega)d\omega = \frac{1}{2}\int_0^{\infty} P(\omega)d\omega \quad (1)$$

$$MNF = \frac{\int_0^{\infty} \omega P(\omega)d\omega}{\int_0^{\infty} P(\omega)d\omega} \quad (2)$$

A previous representative work regarding muscular fatigue compensation of EMG-based interface is a research about a prosthetic hand, named by 'Utah arm' [5]. Here, muscular fatigues generated by repetitive muscle movements (radial flexion motion) are improved by the fatigue compensating preprocessor. And, Winslow et al. [6] proposed a fatigue compensation method using artificial neural networks for functional electrical stimulation (FES) to generate stimulations with suitable intensity at a proper time. However, these results of previous works are based on a specific single muscle movement, not considering various muscle movements together.



(a) DAMV at channel #3



(b) DAMV at channel #4

Fig. 3. Time-dependent feature variations

3. Robust EMG pattern classification against muscular fatigue effect

3.1. An Important observation on muscular fatigue effect

Four assumptions were made in implementing the adaptation process of EMG pattern recognizer compensating muscular fatigue effects. The first assumption is that one recognizer is used by only one user, i.e., we exclude the effect of individual difference. The second assumption is that the locations of EMG electrodes with 4 channels are always fixed as shown in Fig. 2. The third assumption is about a method of the muscle contraction. Sustained motions are considered instead of repetitive muscle movements. And the recovery process is accompanied with the ends of motion.

And the forth assumption is that EMG signals can be quasi-stationary when EMG signals are segmented by short periods [8]. This assumption is verified in Fig. 3. Figure 3 shows the variations of a feature value, Difference Absolute Mean Value (DAMV, see Eq. (3)), dur-

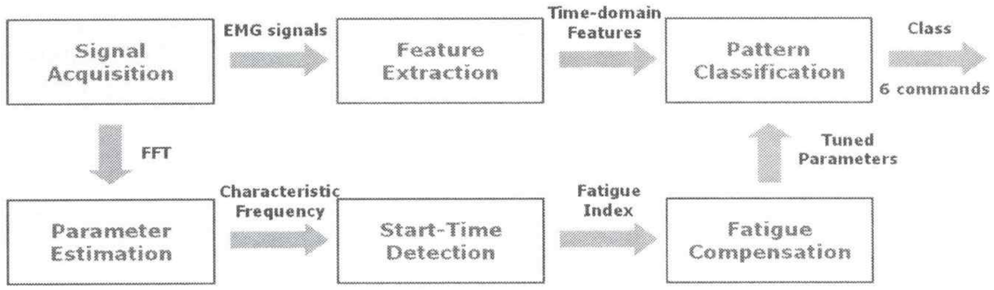


Fig. 4. Block diagram of proposed method

ing 60 sec with one of the six basic motions including the reference motion. Each signal acquisition is repeatedly performed as many as ten times through sustained contractions for each defined basic motion. Here, fatigue effects between adjacent trials can be excluded by assigning three minutes' rest.

Difference Absolute Mean Value (DAMV) [9]

DAMV is the mean absolute value of the difference between adjacent samples and expressed by Eq. (3). Here, N is the size of time-window for computing.

$$DAMV = \frac{1}{N-1}\sum_{i=1}^{N} |x_{i+1} - x_i| \tag{3}$$

Figure 3 shows that the trends of feature variations are consistent. This observation is still the same in four other volunteers' tests. After all, the amount of feature variation from the initial value may be estimated using the contraction time. And, the muscle contraction time may be estimated as the lasting time of human motion based on the third assumption on the continuous muscle contraction. As a result, the degradation in system performance by the muscular fatigue effect can be compensated with differential feature value, DAMV in Fig. 3, by estimating the muscle contraction time via the lasting time of human's motion.

3.2. Robust EMG pattern recognizer

The suggested block diagram of robust EMG pattern recognizer is shown in Fig. 4. In Fig. 4, the above part is a general pattern recognition scheme and the below one is additional adaptation process for robust EMG pattern recognition to the muscular fatigue effect. Here, Except DAMV, three additional features [9], Integral Absolute Value (IAV), Zero-Crossing (ZC), and Variance (VAR), are used for the pattern classification (see Eqs (4),(5) and (6)). And Fuzzy Min-Max Neural Network [10] is adopted as a pattern classification method by its conspicuous on-line learning ability.

FMMNN is a supervised learning classifier that utilizes fuzzy sets as pattern classes. Each fuzzy set is a union of fuzzy set hyperboxes. Fuzzy set hyperbox is an n-dimensional box defined by a min point and a max point with a corresponding membership function. Learning algorithm of FMMNN is the following three-step process [10]:

- *Expansion*: Identify the hyperbox that can expand and expand it. If an expandable hyperbox can't be found, add a new hyperbox for that class.
- *Overlap test*: Determine if any overlap exists between hyperboxes from different classes.
- *Contraction*: If overlap between hyperboxes that represent different classes does exist, eliminate the overlap by minimally adjusting each of the hyperboxes.

$$IAV = \frac{1}{N}\sum_{i=1}^{N} |x_i| \tag{4}$$

$$ZC = \sum_{i=1}^{N} sgn(-x_i x_{i+1}),$$
$$sgn(x) = \begin{cases} 1, & if\ x > 0 \\ 0, & otherwise \end{cases} \tag{5}$$

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N} (x_i - E\{x\})^2 \tag{6}$$

$E\{x\}$ is the mean value for a given segment. And, N is the size of time-window for computing.

In Fig. 4, adaptation process consists of three subparts: parameter estimation, start-time detection, and fatigue compensation.

Parameter Estimation: Two characteristic frequencies, MDF and MNF in Eqs (1) and (2) are calculated with the given signal.

Start-Time Detection: A transition between any two basic motions defined in Fig. 1 naturally goes by ref-

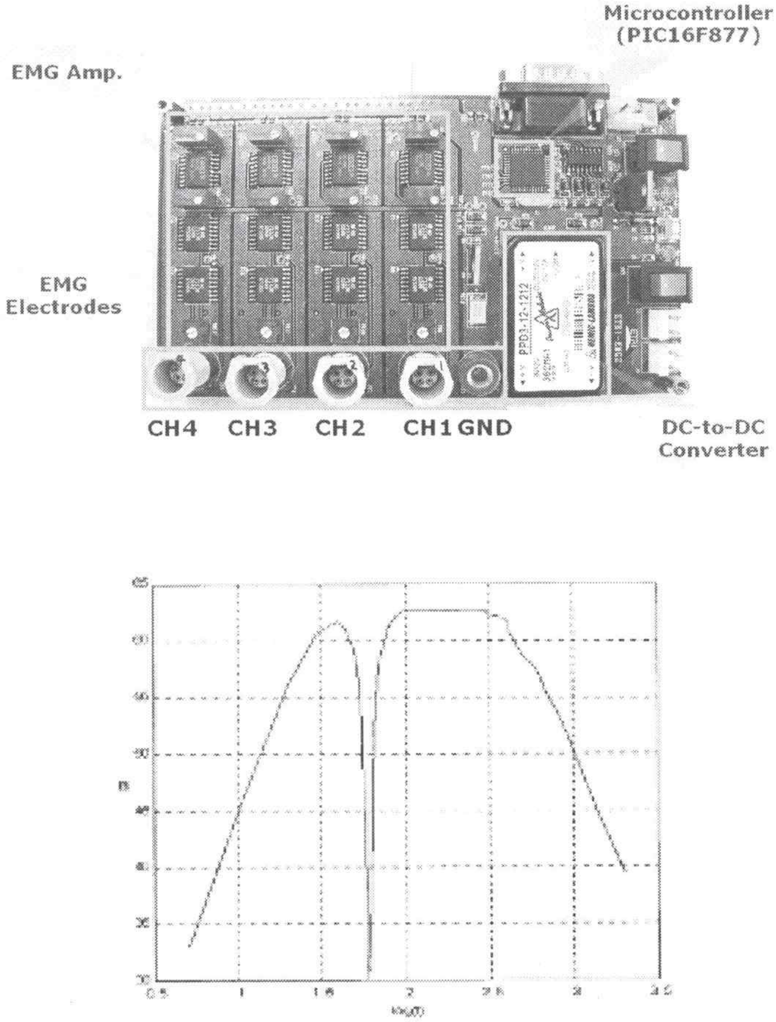


Fig. 5. Developed EMG signal acquisition module and its frequency response

erence posture since reference posture is defined as relaxation posture. Thus, the start-time of muscle contraction for another motion can be found by detecting reference posture. By several experiments on the values of both MDF and MNF for various human motions, a rule described in Eq. (7) has been found and used for detecting the start-time and initializing the time instant of a motion.

If *MDF at channel #3* < 40 *Hz* and *MDF at channel #4* < 40 *Hz* and *MNF at channel #3* < 60 *Hz* and *MNF at channel #4* < 60 *Hz*, then start-time is detected. (7)

Fatigue Compensation: The fatigue compensation is performed simply using the graph in Fig. 3 because the graph in Fig. 3 can be used as a look-up-table to find the amount of compensation at the detected time. Specifically, the proposed fatigue compensation method is to adjust min-max values of hyperboxes in FMMNN according to the consistent feature variation in Fig. 3 for every 2 seconds. After these adjusting, min-max values of hyperboxes are re-adjusted through the learning algorithm of FMMNN, such as expansion, overlap test and contraction. This re-adjustment process is also done for every 2 seconds with the first step. Here, the meaning of 2 seconds is the minimum time period to be able to observe the muscular fatigue effect in EMG signal.

4. Experimental results

4.1. Experimental configuration

The proposed robust EMG pattern classifier was applied to control a powered wheelchair. Five non-handicapped men who have no prior knowledge about experiments were volunteered for this experiment. The objective of experiment was to follow six motions: reference, up, down, left, right, and stop.

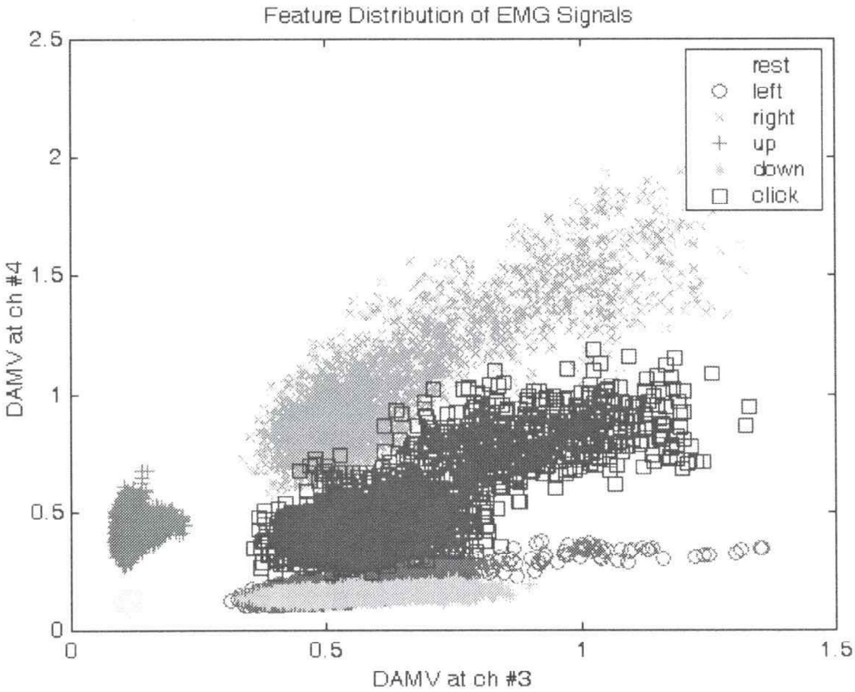


Fig. 6. Feature distribution of EMG signal in two-dimensional space

EMG signals were acquired with a 4-channel EMG signal acquisition module like Fig. 5 which was specially designed for low noise, high gain, ease-to-use and small size. In the frequency response plot of Fig. 5, x-axis means the frequency in log-scale and y-axis means the amplitude in dB scale. Frequency response of the EMG amplifier shows that it guarantees us to obtain the signal (23 Hz–470 Hz) and eliminate the power-line noise (60 Hz).

Delsys DE 2.1 electrode and shielded cable was used to reduce the effect of noise in the environment. Sample rate for signal acquisition was 1 kHz and a size of time-window for analysis was 128 ms. The measured EMG signals are conditioned to pass through 20Hz high-pass filter, 500 Hz low-pass filter and 60Hz Biquad(2nd order) notch filter to be amplified by our developed EMG measurement system with 1360 V/V. This filters guarantees us to obtain EMG signal within the range of 23 Hz–470 Hz and eliminating 60Hz power-line noise sharply by virtue of Biquad notch filter. The amplified EMG signals are converted by A/D converter, PIC16F877 of Microchip, with 1 kHz sampling frequency and with 12 bit resolutions.

The same experiments were performed for five subjects but measured EMG signals were different from each subject due to their own physiological characteristics and slightly different locations of electrodes.

4.2. Experimental results

IAV, ZC, VAR and DAMV are extracted from four channel EMG signals as the features for pattern recognition. Fig. 6 shows a distribution of DAMV (ch. #3 and ch. #4) in two-dimensional feature space.

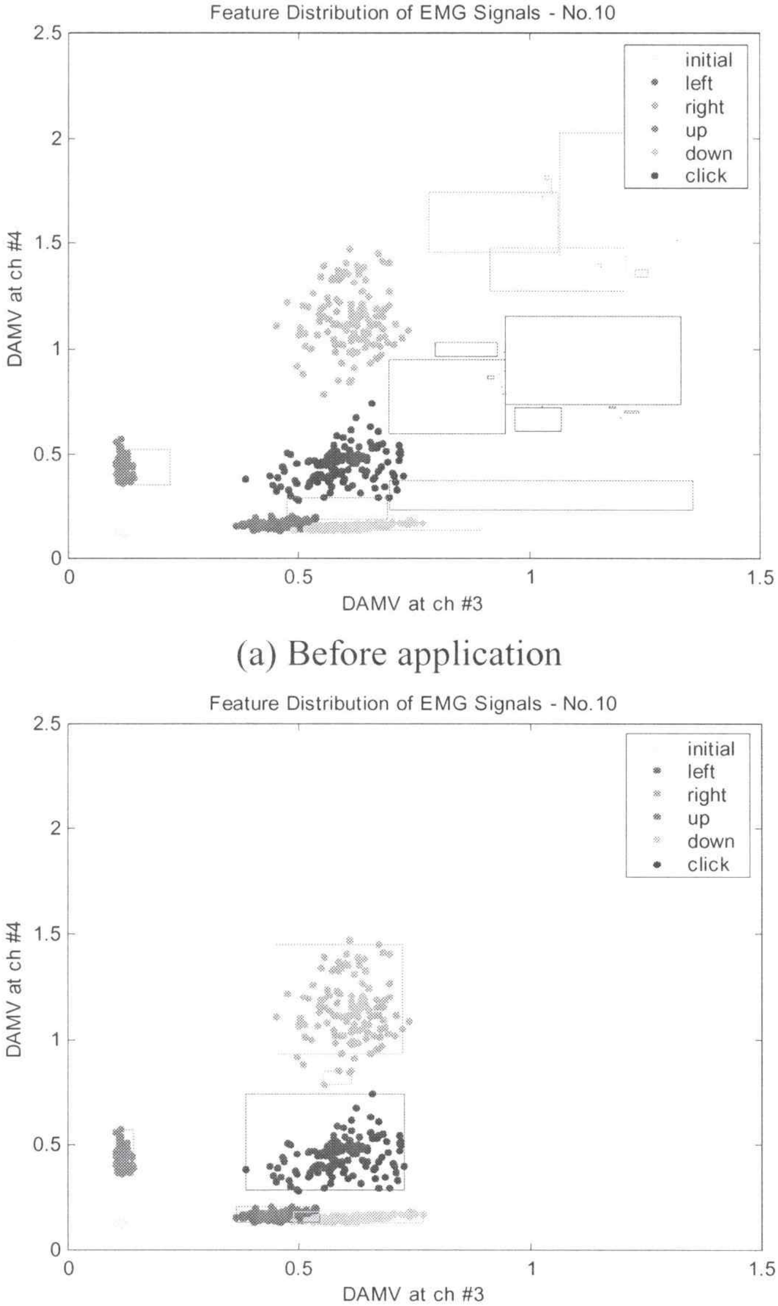
As mentioned above, the trends of feature variations are consistent. Even though feature distributions are varied by sustained time of muscle contractions, class boundaries of FMMNN are correspondingly adjusted by proposed fatigue compensation method. Fig. 7 represents that hyperboxes of proposed method well reflect time-varying feature distributions due to muscular fatigue effects.

Figure 8 refers to pattern classification rates for all users. System performance was highly improved by the proposed method, FMMNN and fatigue compensation, (connected line) compared with FMMNN only (dotted line).

Movement directions according to the predefined basic motions in Fig. 1 are shown in Fig. 9. The designed input pattern and the corresponding plot of characteristic frequency, MNF, are also shown in Fig. 9.

Bold points in Fig. 9 represent detected start-times of motions. If a muscle contraction is sustained, the trends of characteristic frequency toward lower frequency are obviously observed.

Figure 10 shows the developed interface for controlling powered wheelchair and its rehearsal. While



(a) Before application

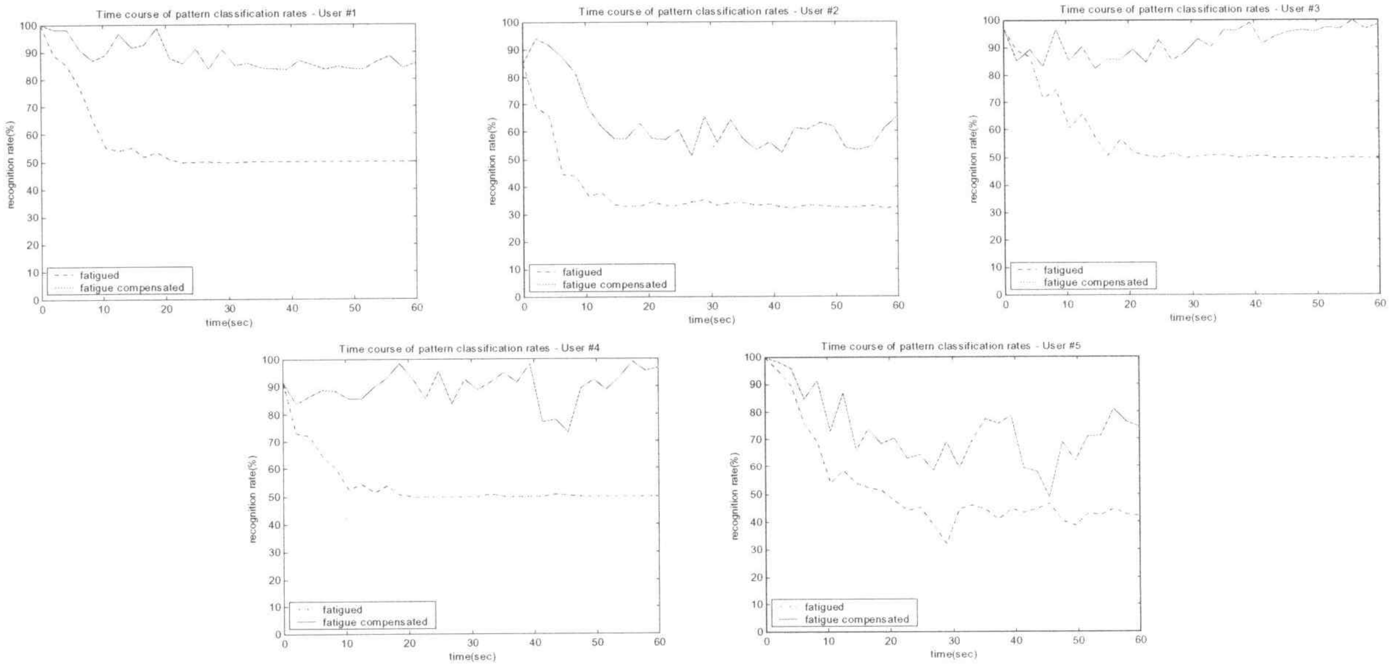
(b) After application

Fig. 7. Comparison of class boundaries

the user takes one of the pre-defined actions, the interface displays the real-time EMG signals in time and frequency domain, and the classification results with colored arrows.

5. Conclusion

As a means of controlling a powered wheelchair, a novel muscular fatigue compensation method is proposed for EMG-based pattern classification. For that purpose, the important observation was made that feature variations for duration of muscle contractions are consistent. Based on this observation, we propose the strategy which is to adjust min-max values of hyperboxes according to the contraction time using learning algorithm of FMMNN. As a result, we confirmed that a significant improvement was made in terms of pattern classification rates, and thus confirmed that the proposed method is adequate to controlling the powered wheelchair.



(a) user #1 (b) user #2 (c) user #3 (d) user #4 (e) user #5

Fig. 8. Fatigue compensated pattern classification rates for multiple users

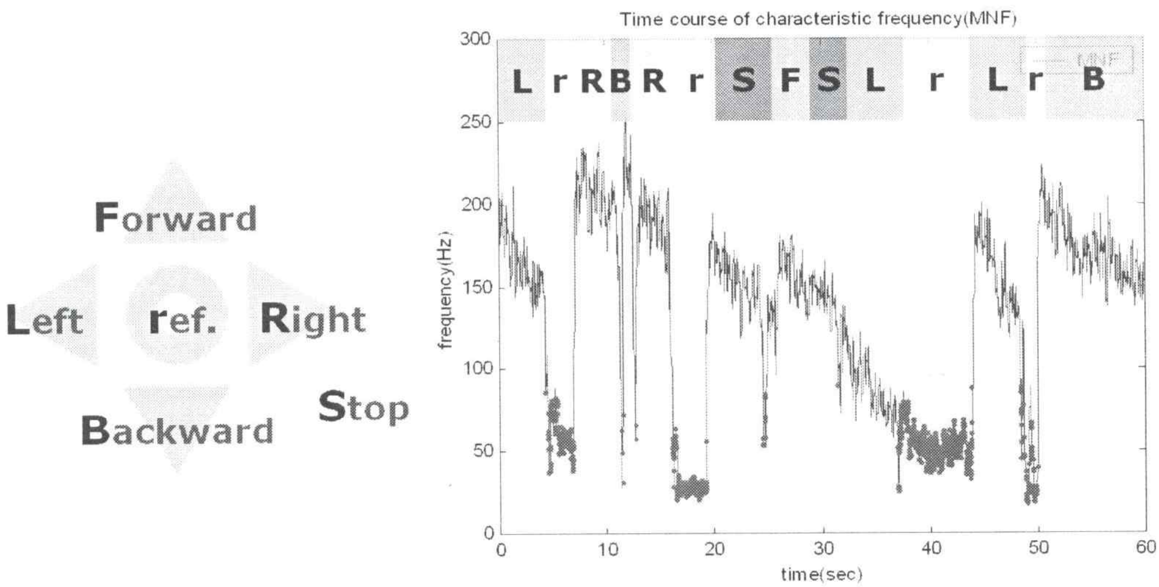


Fig. 9. Designed input pattern and the variation of characteristic frequency (MNF at CH #3)

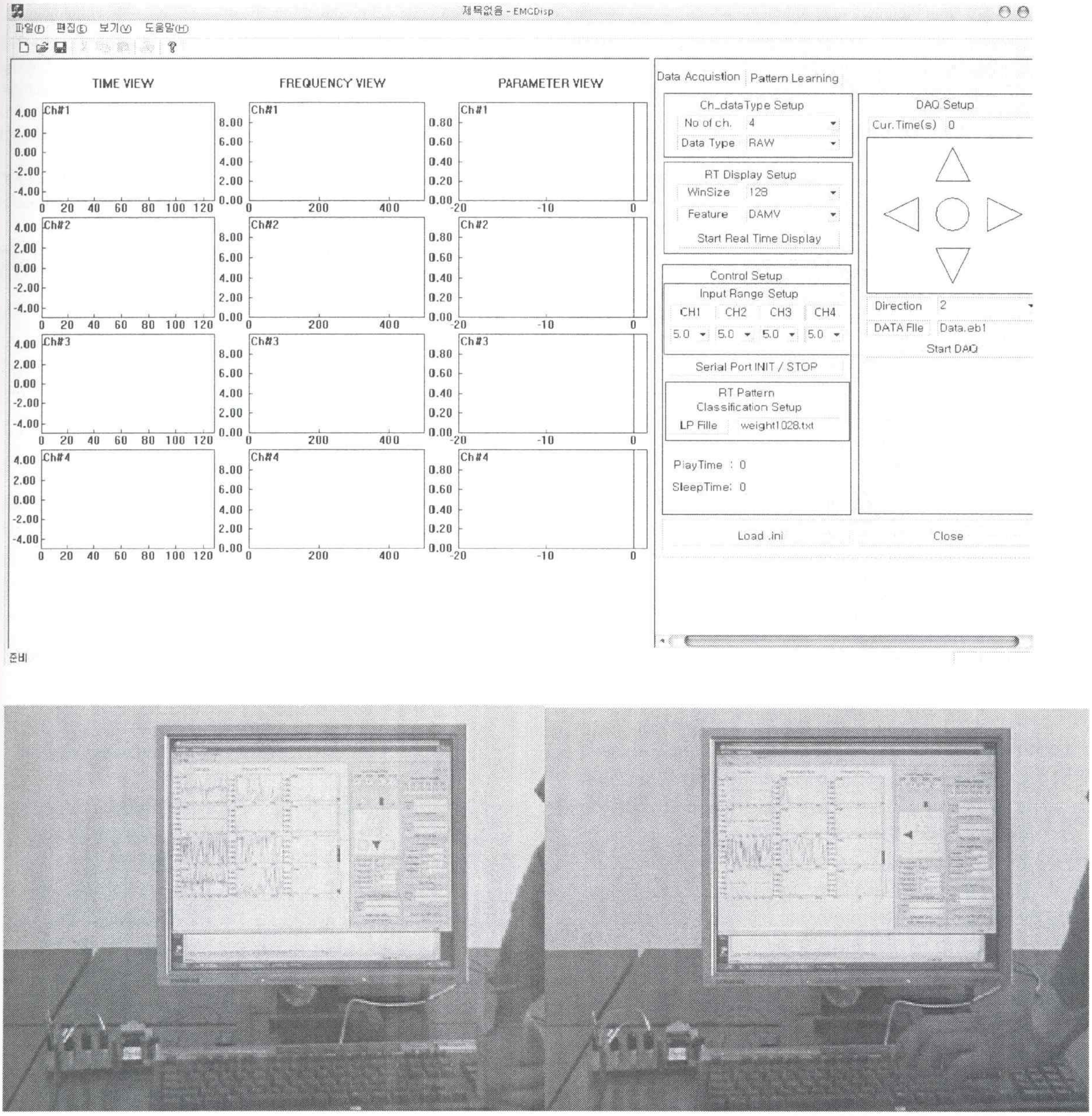


Fig. 10. EMG-based control interface for powered wheelchair and its rehearsal

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