Towards Enhancement of Patients' Engagement: Online Modification of Rehabilitation Training Modes Using Facial Expression and Muscle Fatigue

Jiaxing Wang, Weiqun Wang, Zeng-Guang Hou, Xu Liang, Shixin Ren, Liang Peng

Abstract— **Rehabilitation training combined with human psychological and physiological information can enhance patients' neural engagement. For this purpose, a facial expression and muscle fatigue based rehabilitation training method is proposed in this paper. Signals from major zygomaticus and corrugator supercilii muscles are used for facial expression recognition, and signals from rectus femoris and biceps femoris muscles are used for fatigue level analysis. Facial expressions (positive, neutral, and negative) are recognized by a classifier which is constructed by wavelet packet features and neural network, and median frequency (MF) is applied to analyze fatigue level. A passive training mode and five-level active training modes are included. Different training modes have different damping levels. When the patient is with positive expression and without fatigue, the damping will be raised automatically in order to increase exercise difficulties and enhance the patient's engagement; when with negative expression and mild fatigue, damping will be decreased properly to reduce exercise difficulties and ease user's burden to obtain more efficient training. Moreover, when patient is severe fatigue, passive training is selected to avoid overfatigue and muscle injury. Feasibility of the proposed method is validated by the experiment conducted on the platform of a damping adjustable treadwheel.**

I. INTRODUCTION

Enhancing patient's neural engagement plays an important role in improving the functional outcome of technology-assisted rehabilitation [1]. Many methods, including motor imagery [2] and steady state visual evoked potential (SSVEP) [3] based brain computer interfaces (BCI) and virtual reality [1], have been introduced for this purpose. Affection computing can also be used to enhance neural engagement by monitoring and optimizing emotional states [4]. In the traditional training mode modification methods (eg. rehabilitation training modes adjusted by the patient's motion intention [5]), patients' psychological or physiological change usually hasn't been considered, which will lead to low engagement and inefficient training. Facial expressions can reflect emotional states and can be used to modify training modes to maintain or improve engagement; muscle fatigue information can embody patient's training intensity, thus it can be used to avoid overfatigue and muscle injury. Therefore, these two kinds of signals are applied to modify training modes, and to improve patients' neural engagement accordingly.

Facial expression, a non-verbal psychological signal, plays an important role in social information exchange [6]. A number of factors, such as emotion elicitation and labeling methods, can affect the recognition precision and should be considered. Several approaches based on image processing or video analysis have been used to capture and analyze patients' facial expression [7][8][9]. The limitation of these methods is that they require cameras placed towards patients' faces, and the recognition performance is easily affected by the light quality. Human physiological signals, especially electroencephalogram (EEG) and sEMG, have also been used for facial expression recognition. On one hand, EEG signals can reflect the user "inner" ture emotions, but the signals are too weak (microvolt level) and easily disturbed by environment and internal noise (e.g. emotional fluctuation and artifacts). On the other hand, sEMG method is more efficient and robust due to the higher amplitude (0-10 millivolt) and broader bandwidth (0-500 hz); moreover, compared to the methods based on image processing or video analysis, the high temporal resolution attribute of sEMG signals also makes it suitable for emotion recognition. Thus, sEMG sensors are used to capture facial expressions at real time in this paper.

During the rehabilitation training session, muscles may be injured because of the overfatigue caused by excessive amount of exercises and the inappropriate postures. Several methods have been introduced for the detection of muscle fatigue. Muscle stiffness sensors (MSS) can be used to measure the change of the stiffness signals under different muscle fatigue conditions, thus can be used to analyze the fatigue levels, but muscle stiffness signals are less sensitive to muscle fatigue than other biosignals [10]. The analysis of amplitude or frequency of sEMG signals can also be used to detect muscle fatigue [11]. It has been proved that, with the level of fatigue increasing, the amplitude of the sEMG signal will get bigger and the median frequency (MF) will move towards lower frequency areas. This phenomenon can be used to detect the occurrence of muscle fatigue.

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This paper presents a novel method for online modification of training modes, which is based on patients' facial expression and muscle fatigue information and has potential to increase the engagement of patients. In section 2, the way of data acquisition and signal denoising is introduced firstly; then, a classifier for real-time facial expression recognition is constructed by wavelet packet features and neural network; moreover, the methods for muscle fatigue evaluation are explained; modification scheme of the training modes is introduced finally. A damping adjustable treadwheel is used to conduct the experiment in section 3, based on which feasibility of the proposed method is validated. In section 4, a brief discussion and future works are presented.

II. Material & Methods

A. Data Acquisition and Signal Denoising

Delsys Trigno™ IM sensors are used to collect sEMG data. Every electrode is equipped with a sEMG sensor and an inertial measurement unit (IMU). The former is used to record wireless sEMG signals with 1111.11 hz sample rate, and the later is used to record inertial measurements such as acceleration. In the experiment, data acquired from sEMG sensors are used for facial expression recognition and muscle fatigue detection. Two electrodes are placed on the major zygomaticus muscle and corrugator supercilii muscle for smiling and frown recognition respectively [12]; the other two electrodes are placed on the rectus femoris and biceps femoris muscle for lower limb fatigue analysis [13]. Some precautions should be taken into account in order to get high quality signals. For example, the skin areas for placing electrodes should be cleaned to improve the signal-to-noise ratio.

Four healthy subjects (3 males and 1 female, aged between 22 and 25 years old) participated in the experiment. It is required that the subjects should have a good rest the day before experiment. The facial expression and muscle fatigue signals during treadmill training were recorded respectively (facial expression: 20 sets of data per subject, 1.5 seconds per set; fatigue signal: the subjects performed treadmill training until exhausted, ensuring that severe muscle fatigue occurred). The raw signals are band-passed filtered by a six-order butterworth filter with a frequency band between 10 hz and 400 hz which can cover the most important sEMG spectrum [14], and slow transients can also be reduced. Then a six-order butterworth bandstop filter is applied to filter out 50 hz power frequency interference.

B. Facial Expression: Feature Extraction and Classification

Referring to the previous research [15], wavelet packet (WP) features and a three-layer neural network (NN) are used to construct the classifier to obtain the high classification accuracy in this paper.

After denoise processing of the two-channel facial expression signals, these data are decomposed by a 3-order wavelet packet firstly. Then the first three root nodes of each channel, which can reconstruct signals with frequency band between 0 hz and 416.7 hz, are reserved (total nodes = channel number $\times$ nodes/channel = 6). WP energy value of each node is calculated finally and saved as the neural network input data. For channel m, WP energy value (EV) of the node n is calculated by

$$EV(m,n) = \sum_i |(node_i(m,n))| \tag{1}$$

where $node_i$ represents the *i*th data of the node. And for the three-layer NN, it has one input layer with 6 neurons, one hidden layer with 10 neurons, and one output layer with 3 neurons. The transfer functions are logsigmoid for hidden layer and purelin for output layer.

C. Evaluation of Muscle Fatigue

As a good response to the patient's engagement and training intensity, muscle fatigue conditions should be monitored at real time to avoid overfatigue and muscle injury. Based on the previous work [11], MF, a frequency-domain analysis method, is applied to estimate the fatigue level. After the signal denoising, the time-domain signals are converted into frequency-domain signals by fast Fourier transformation (FFT) firstly. Then power spectral density (PSD) and MF were calculated in turns. For signal s(t), the MF can be calculated as follows [11]:

$$psd(f) = |fft(s(t))|^2 = \left| \int_{-\infty}^{+\infty} s(t)e^{-j2\pi ft}dt \right|^2 \tag{2}$$

$$\int_0^{MF} psd(f)df = \int_{MF}^{\infty} psd(f)df = \frac{1}{2}\int_0^{\infty} psd(f)df \tag{3}$$

After MF calculation, a 10-order polynomial fitting method based on least mean square criterion is applied for fatigue condition analysis.

Relative change rate of the MF (ΔMF) is applied to quantify muscle fatigue.

$$\Delta MF(t) = \frac{MF(t_0) - MF(t)}{MF(t_0)} \tag{4}$$

where t_0 means the time of start training and t means the duration of the experiment.

D. Adjustment Scheme of Training Modes

Passive training and five-level active training are included in the training modes. In the passive training, rehabilitation robot will run with a fixed velocity. And in the active training, with the training level increased (level 1 to 5), the damping will be raised gradually (level 1 to 5). The training modes are determined by the subject's facial expression and muscle fatigue level, and the specific modification strategy are given in table I.

According to [16][17] and subject's description about fatigue feeling during the experiment, we defined that mild fatigue occurred when ΔMF is greater than 0.21, and sever fatigue occurred when ΔMF is greater than 0.35.

Once severe fatigue is detected, passive training mode will be chosen regardless of subject's facial expression, in order to avoid the occurrence of overfatigue which can lead to muscle injury.

TABLE I
RELATIONSHIP AMONG FACIAL EXPRESSIONS, MUSCLE FATIGUE AND TRAINING MODES (TM)

TM \ Fatigue / Expression	Without fatigue	Mild fatigue	Severe fatigue
Positive	Up+	Keep	Passive training
Neutral	Keep	Keep	Passive training
Negitive	Down-	Down- -	Passive training

Note: "Keep" means keep the current training level; "Up+" / "Down-" means increase or decrease training one level; "Down- -" means decrease training two levels.

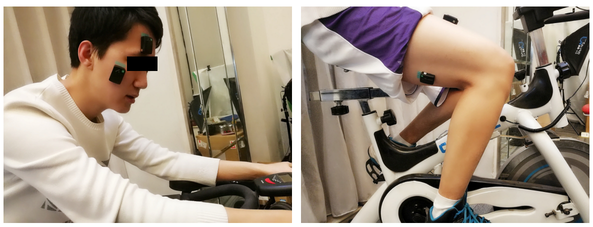

Fig. 1. The placement of the electrods in treadmill training

As for active training, the relationship among force (F) imposed by patient, system damping (d), and velocity (v) can be given by :

$$v = \frac{F}{d} \tag{5}$$

It can be seen from (5) that, with the damping increasing, patients need to apply a greater interaction force to maintain the current training velocity. Consequently, in the modification of training modes, when user is with positive emotion and without fatigue, the damping will be increased one level automatically in order to increase exercise difficulties and enhance patients' engagement; when with negative expression and mild fatigue, damping will be decreased two levels to reduce exercise difficulties and ease user's burden to obtain more efficient training.

III. EXPERIMENT AND RESULT

A. Experiment Setup

A treadwheel is used in this experiment and its damping is adjustable. Prior to the experiment, four EMG electrodes were placed on the subjects' faces (major zygomaticus and corrugator supercilii muscles) and legs (rectus femoris and biceps femoris muscles), and the actual electrodes' placement is given by Fig. 1. Subjects are asked to do treadmill training and signals captured by the EMG electrodes are recorded at real time.

System control block diagram is given in Fig. 2. First, the four-channel signals, which have been denoised by filters, are segmented by sliding windows (facial expression: a 800 ms sliding window with 150 ms offset; muscle fatigue: a 30 s sliding window with 15 s offset). Then, the real-time facial expression data segment is imported into the trained classifier to identify the expression, meanwhile, the muscle fatigue level is calculated by (4). Finally, according to the result of facial expression recognition and muscle fatigue level, the training mode (passive training or five-level active training) is adjusted at real time according to table I.

B. Results

One of the volunteers' real-time parameters variations are shown in Fig. 3. First, the default training mode is active training, and damping level is three. Except the moments when local details of the facial expression signals are shown, the subject is detected with neutral expression and without or mild fatigue, thus the damping level is maintained all the time. At the time of 1.3 minutes, subject is detected with positive expression and without fatigue, so the damping level is increased one level. The other conditions at the 5.6, 9.8, 14.1 or 19.2 minutes can also be explained by table I. Particularly, at the minutes of 9.8, the damping has reached its maximum level. Even though positive expression is detected, the damping level is still maintained instead of increased. From Fig. 3 we can see, severe fatigue is not occurred for the volunteer during the 20-min treadmill training, thus passive training mode is not be used in this exercise. Combining subject's current facial expression and muscle fatigue condition, training modes of the treadmill can be switched smoothly by subjects at real time.

IV. DISCUSSION & FUTURE WORK

An online modification of training modes, which is based on facial expression and muscle fatigue information, is presented in this paper. To enhance patients' engagement, the previous research mainly focused on monitoring and improving patients' emotion or facial expression during the training, and patients' muscular capacity is rarely taken into account simultaneously, which will inevitably leads to overfatigue. For example, some patients are too eager to recovery, even when their muscle is overfatigue or injury, they can still keep in a good mood to proceed with rehabilitation training, and this condition can be avoided in our proposed method.

Affection computing has been widely researched, however patients' specific emotion inducement or labeling methods during rehabilitation training, are relatively less studied. Patients' emotions are very complex and closely related to the actual training environment and methods. General emotion induced methods (such as music-induced, picture-induced, or video-induced methods) are difficult to induce patients' real emotion during rehabilitation training well. Some new paradigms should be investigated for patients' emotion induction and labeling. What's more, detailed method to quantify muscle fatigue conditions will be carried out in the future to accurate understand patient's physical states. Realization of the proposed method in our lower limb rehabilitation robot will also be conducted in the future.

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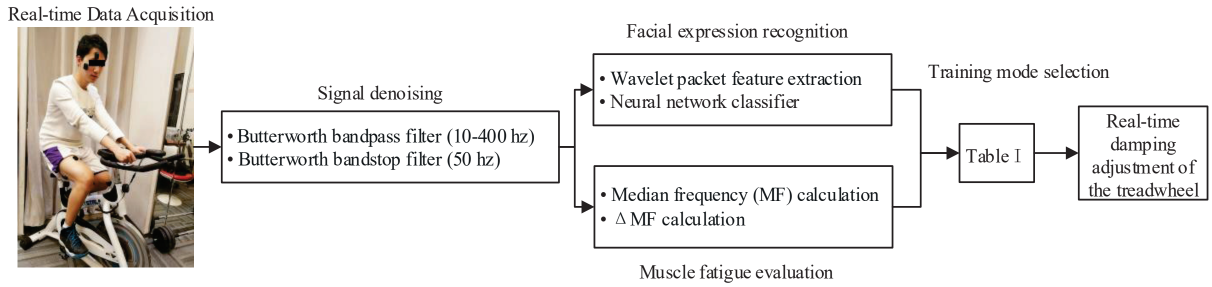

Fig. 2. System control block diagram

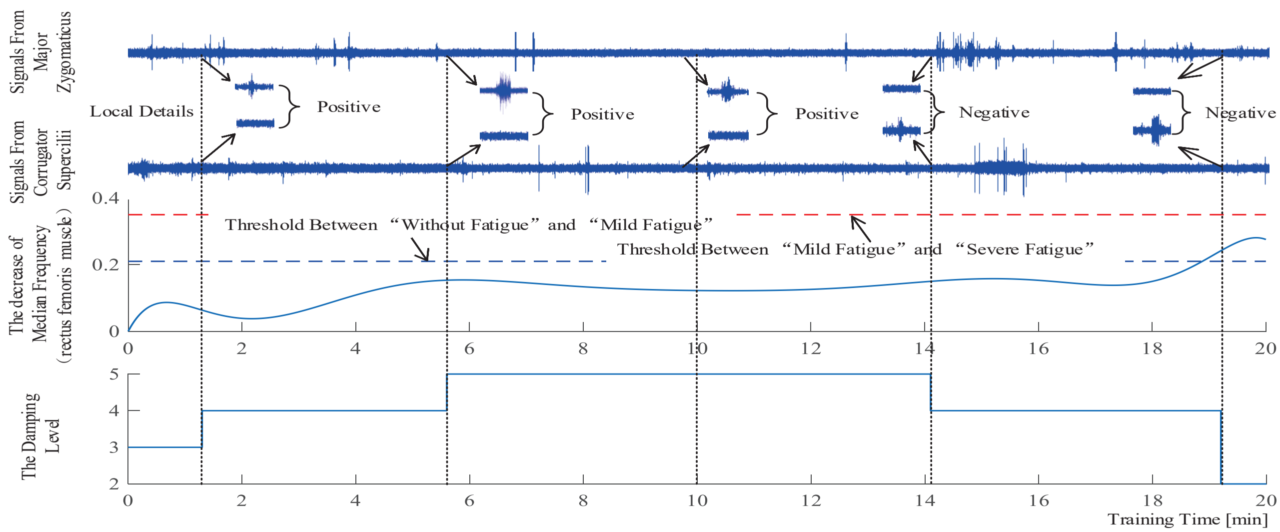

Fig. 3. The real-time parameters variation diagram of one volunteer during 20-min treadmill training

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