Direct Rehabilitation System Using Probabilistic Neural Networks*

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***Abstract*—In this paper, we propose a joint movement transmission system using FES based on a parallel-type discrimination structure for electromyography (EMG) signals to support effective rehabilitation. In experiments, we conducted the intervention using the proposed system and quantitatively evaluated the effect of functional reconstruction. The results showed that the proposed system improved motor function and reduced joint pain and muscle tension, suggesting that it may be an effective rehabilitation system for paralyzed patients.**

***Index Terms*—functional electrical stimulation, motion estimation, neural networks, AI-based rehabilitation system**

I. INTRODUCTION

Various rehabilitation programs have been provided to stroke patients to reconstruct the upper limb functions required to return to daily life and social activities. However, the provision of verbal or manual guidance by therapists is challenging, underscoring the necessity for objective and quantitative assessment and intervention strategies [1].

To solve these problems, rehabilitation using robots and functional electrical stimulation (FES) has been proposed [1]. In rehabilitation using FES, peripheral nerves are electrically stimulated to induce muscle contraction and patient movement. In addition, we proposed a human-to-human joint motion transmission system using FES and electromyography (EMG) signals [2]. This system supports rehabilitation by intuitively communicating and teaching the joint motion and muscle contraction state by estimating the motion based on EMG signals and providing an FES that reproduces the motion. However, because this method extracts global amplitude information from the EMG signal for identification, the responsiveness of the motion transmission is reduced and the user's sense of agency may be impaired.

In this paper, we focus on the electromechanical delay of the EMG signal and propose a discrimination model that connects a transition state discriminator that uses the waveform length of the signal as a feature and a steady state discriminator that uses amplitude information in a stepwise manner. This model enables fast and stable motion transfer, and effective training can be performed without impairing the user's sense of agency.

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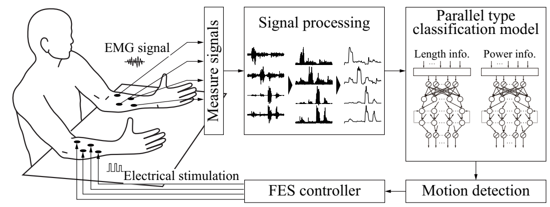


Fig. 1. Concept of the EMG-driven FES rehabilitation system.

II. PROPOSED SYSTEM

The concept of the proposed EMG-driven FES rehabilitation system is illustrated in Fig. 1. EMG signals are measured and smoothed amplitude patterns and waveform length patterns are calculated as feature vectors. The user's motions are probabilistically estimated using probabilistic neural networks, and motion transfer is realized by applying electrical stimulation to the muscle group to induce the estimated motion.

A. Signal processing and feature extraction

The EMG signals measured from I pairs of electrodes attached to the user are A/D converted (sampling frequency: f_s Hz), and $E_i(t)$ is obtained using a second-order Butterworth bandpass filter (cutoff frequency: f_c^{low}, f_c^{high} Hz) to extract the effective frequency components of the EMG signals. Next, each signal is full-wave rectified and smoothed by a second-order low-pass Butterworth filter (cutoff frequency: f_c) to compute E_i'. Then, $E_i'^{\mathrm{st}}(t)$ at rest is excluded, and $E_i^{\mathrm{norm}}(t)$ is determined by normalizing with the maximum value of each channel. The smoothed amplitude pattern $\boldsymbol{x_a}(t) = [x_{a1}(t), x_{a2}(t), \ldots, x_{ai}(t), \ldots, x_{aI}(t)]^T$ is calculated by normalizing $E_i^{\mathrm{norm}}(t)$ so that all channels sum to 1.

The sum of the window width M samples for the distance between two points $D_i(t) = |E_i(t) - E_i(t-1)|$ is calculated as the waveform length $T_i(t)$. Then, the length is normalized by the maximum value to obtain $T_i^{\mathrm{norm}}(t)$. The waveform length pattern $\boldsymbol{x_l}(t) = [x_{l1}(t), x_{l2}(t), \ldots, x_{li}(t), \ldots, x_{lI}(t)]^T$ is calculated by taking the maximum value of N samples of the window width for the $T_i(t)$.

B. Motion estimation

In motion estimation, discrimination is conducted using a transition state discriminator using a waveform length pattern $\boldsymbol{x_l}(t)$ and a stationary state discriminator using a smoothed amplitude pattern $\boldsymbol{x_a}(t)$. The transition state discriminator consists of a probabilistic neural network with I-dimensional input and $C+1$-dimensional output, and a posterior probability vector $\boldsymbol{P}_{\mathbf{tran}}$ of C-class motion and rest class is calculated from the transition of the initial EMG signal by inputting $\boldsymbol{x_l}(t)$. On the other hand, the steady state discriminator consists of a probabilistic neural network with I-dimensional input and C-dimensional output, and the posterior probability vector $\boldsymbol{P}_{\mathbf{st}}$ of the C class motion is calculated by inputting $\boldsymbol{x_a}(t)$. The posterior probabilities are combined by the transition time t_m and an arbitrary pre-determined steady state transition time α, and the model posterior probability $\boldsymbol{P}(t)$ as follows:

$$\boldsymbol{P}(t) = \begin{cases} \boldsymbol{P}_{\mathrm{tran}}(t) & \text{if } t_m \geq \alpha, \\ \boldsymbol{P}_{\mathrm{st}}(t) & \text{if } t_m < \alpha, \end{cases} \tag{1}$$

where the transition time t_m is increased when the transition state discriminator is discriminated as an arbitrary motion class and takes the value 0 when it is discriminated as a resting class.

The maximum class of posterior probabilities $\boldsymbol{P}(t)$ is estimated as the movement performed by the user, and the joint movement is realized by applying FES to the muscle group that induces the corresponding movement. This enables fast and stable motion transfer and effective training for the user.

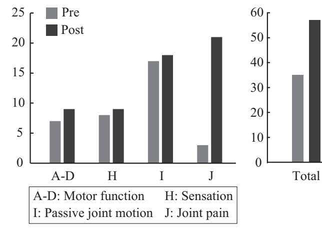
III. Exprements

The number of subjects in the experiment was five, but due to space limitations, this paper details the results of the intervention for a stroke patient in his 70s. The subjects had been left hemiplegic for 4.5 years and had contractures of the left hand joints and fingers.

The EMG signals were measured using an integrated measurement device Sensor I/F SI1000 (Oisaka Electronic Equipment Ltd.) and a wet two-pole electrode, which was applied to the skin surface of the flexor carpi radialis and extensor carpi ulnaris muscles on the non-paralyzed side ($I = 2$). The sampling frequency was set to 1000 [Hz], and the parameters of the proposed signal processing method were $f_c^{\mathrm{low}} = 1$[Hz], $f_c^{\mathrm{high}} = 250$[Hz], $f_c = 1$[Hz], $M = 80$, $N = 80$. Stimulation electrodes were applied to the subjects by trial and error, based on anatomical knowledge of the positions of the target muscles, to induce flexion and extension. Three discrimination classes were defined and estimated: hand flexion, hand extension, and resting state using probabilistic neural networks [3].

The Modified Ashworth Scale (MAS), an evaluation method of muscle tone, and the Fugl-Meyer Assessment (FMA) for upper limb scores, a comprehensive evaluation method of motor function impairment, were measured in the subjects before and after the intervention. Training consisted of 15 minutes of training with the proposed system two days a week for 12 weeks. Figure 2 shows the scenes during training. The subject is able to perform bilateral movements triggered by his own movement, since the movement of the non-paralyzed side is transmitted to the paralyzed side by electrical stimulation. The experiments were conducted under the approval of the Ethics Committee of Fukuyama Memorial Hospital (Approval No. 20231001).

Fig. 2. An example of the experimental scene.



(a) FMA

Muscle Group	Pre	Post
Shoulder flexors	0	0
Shoulder extensors	1	1
Shoulder abductors	1	0
Shoulder adductors	0	0
Elbow flexors	0	0
Elbow extensors	1	1
Wrist flexors	0	0
Wrist extensors	1+	1+
Finger flexors	0	0
Finger extensors	1+	1

(b) MAS

Fig. 3. Clinical scores measured before and after intervention.

Figure 3(a) presents the outcomes of FMA conducted pre and post assessments. The results showed that all scores for motor function (A-D), sensation (H), passive joint motion (I), and joint pain (J) were improved by the intervention. The major improvement was seen in joint pain (J), with the total upper extremity score increasing from 35/126 to 57/126. The FES intervention is known to reduce upper extremity pain [4], and the proposed method may have had a similar effect.

The MAS results for the pre and post assessments are shown in Figure 3(b). The results show that the scores for shoulder abductors and hand extensors improved. In particular, hand extension is a movement induced by the FES, suggesting that muscle tone may have decreased due to the external induction of muscle contraction.

IV. Conclusion

In this paper, we proposed a FES rehabilitation system based on motion estimation. The experimental results showed that the proposed system improved motor function and reduced joint pain and muscle tension, suggesting that it could be an effective rehabilitation system. In future studies, we plan to increase the number of subjects and conduct a detailed investigation of the rehabilitation effects of the proposed system by comparing it with other rehabilitation methods.

References

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