Temporal muscle synergy features estimate effects of short-term rehabilitation in sit-to-stand of post-stroke patients

Ningjia Yang[1], Qi An[1], Hiroki Kogami[1], Kazunori Yoshida[1], Hiroshi Yamakawa[1], Yusuke Tamura[1], Shingo Shimoda[3], Hiroshi Yamasaki[3], Moeka Sonoo[3], Matti Itkonen[3], Fady Shibata-Alnajjar[3], Noriaki Hattori[2], Makoto Kinomoto[2], Kouji Takahashi[2], Takanori Fujii[2], Hironori Otomune[2], Ichiro Miyai[2], Atsushi Yamashita[1] and Hajime Asama[1]

Abstract— **Sit-to-stand (STS) motion is an important daily activity and many post-stroke patients have difficulty in performing the STS motion. Post-stroke patients who can perform STS independently, still utilize four muscle synergies (synchronized muscle activation) as seen in healthy people. In addition, temporal muscle synergy features can reflect motor impairment of post-stroke patients. However, it has been unclear whether post-stroke patients improve their STS movements in short-term rehabilitation and which muscle synergy features can estimate this improvement. Here, we demonstrate that temporal features of muscle synergies which contribute to body extension and balance maintenance can estimate the effect of short-term rehabilitation based on machine learning methods. By analyzing muscle synergies of post-stroke patients (n=33) before and with the intervention of physical therapists, we found that about half of the patients who were severely impaired, improved activation timing of muscle synergy to raise the hip with the intervention. Additionally, we identified the temporal features that can estimate whether severely impaired post-stroke patients improve. We conclude that temporal features of muscle synergies can estimate the motor recovery in short-term rehabilitation of post-stroke patients. This finding may lead to new rehabilitation strategies for post-stroke patients that focus on improving activation timing of different muscle synergies.**

I. INTRODUCTION

Stroke is one of the major leading causes of disability [1]. The absolute number of post-stroke patients is increasing because of the world's aging population [2]. As one of the most common causes of long-term disability, stroke causes global economic burdens [3]. Stroke survivors often present sensorimotor impairments that limit them from doing daily activities such as walking [4], standing [5] and performing sit-to-stand (STS) [6]. To help the post-stroke patients improve their STS motion, many rehabilitation strategies and robotic training devices have been developed. Langhorne et al. showed that repetitive task training strategies could significantly improve the ability to perform STS [7]. However, it was also mentioned that there is a lack of research investigating the effects of specific training protocols especially for severely impaired post-stroke patients [8].

At present, robotic devices are designed to be used in rehabilitation to decrease the burden on physical therapists (PTs). By decreasing the burden on PT, the number of repetitions and time duration in training sessions can be increased. Hence, robotic devices became an alternate intervention for rehabilitation in sit-to-stand, locomotion, posture control, and so forth. A number of robotic devices ranging from unilateral, single joint training to bilateral, multi-joints association were developed. Even so, there has been a lack of evidence on the effects of different robotic devices on rehabilitation in post-stroke patients [9]. In addition, Burnfield et al. suggested that some device-assisted training might be unsuitable compared to clinician-assisted training [10]. Therefore, studying intervention of PTs may also help to adjust strategies of robotic interventions.

The present paper analyzed post-stroke patients who performed STS with a specific intervention of PTs; this intervention was defined as short-term rehabilitation. The improvements in STS performances of post-stroke patients were defined as motor recovery. In our previous study, we analyzed 33 post-stroke patients with different motor severities and found that timing activation of muscle synergy which contributed to hip rising primarily reflected motor impairment [11].

Since stroke causes lesions in the central nervous system that may essentially affect the central controllers, it leads to abnormal coordination of muscles and impaired biomechanical outputs. Investigating the abnormal muscle coordination of post-stroke patients in STS should aid development of new rehabilitation strategies for further motor recovery. Hence, our study employed the concept of muscle synergy to analyze the STS of post-stroke patients during short-term rehabilitation.

Muscle synergy decomposed the complex control of individual muscles into modular organization [12]. Related studies showed that the muscle activation of human motor behaviors, such as locomotion [13] and STS [16], could be explained as the linear-summation of a small number of muscle synergies. Clark et al. suggested that the decreased

[1]Ningjia Yang, Qi An, Hiroki Kogami, Kazunori Yoshida, Hiroshi Yamakawa, Yusuke Tamura, Atsushi Yamashita and Hajime Asama are with the Department of Precision Engineering, The University of Tokyo, Tokyo, 113-8656, Japan yang@robot.t.u-tokyo.ac.jp

[2]Kouji Takahashi, Makoto Kinomoto, Noriaki Hattori, Takanori Fujii, Hironori Otomune and Ichiro Miyai are with Morinomiya Hospital, Osaka, Japan

[3] Shingo Shimoda, Hiroshi Yamasaki, Moeka Soono, Matti Itkonen and Fady Shibata-Alnajjar are with RIKEN Brain Science Institute, Japan

muscle synergy numbers in human locomotion led to the more compensatory walking strategies used by post-stroke patients [13]. For human STS movements, our research group employed both forward dynamic simulation [16] and measurement experiment [17] to clarify the muscle synergy structure in young adults, and post-stroke patients with the interventions of PTs [18].

Our previous study found that activation timing of the muscle synergy to raise the hip can reflect the motor impairment of mild and severe post-stroke patients. This previous study also developed a classifier that could evaluate if severe patients improved their STS motion [11]. Motor impairment caused by stroke limited the function in muscle control and affected the control of movement of arm and leg of the affected side. Therefore, many stroke rehabilitation studies, particularly the work of physiotherapists and occupational therapists, focus on the motor recovery of impaired movement [7].

The first aim of this study was to evaluate the motor impairment of post-stroke patients performing STS with the intervention of PTs. We used the motor impairment classifier developed in our previous study [11] to evaluate whether the trials with PTs' interventions were classified as better motor performance than trials without PT intervention. The second aim was to identify the crucial temporal features that could estimate whether motor ability recovers from short-term rehabilitation of severe post-stroke patients. We hypothesized that temporal features of muscle synergies could estimate the motor recovery in short-term rehabilitation of severe post-stroke patients. During the short-term rehabilitation, it has been found that some severe post-stroke patients could improve their STS and other severe patients might show little improvement. We hypothesized that specific temporal features were able to estimate whether the severe patients could improve during the short-term rehabilitation. These features may provide information for the development of new rehabilitation strategies suitable for individual motor recovery.

II. Evaluation of Motor Impairment in Short-Term Rehabilitation

A. Muscle Synergy Model

Human STS motion is a result of multi-joint movements achieved by muscle coordination. The muscle synergy model expressed muscle activation as a linear summation of spatiotemporal patterns (Eq. (1)):

$$\mathbf{M} = \mathbf{W}\mathbf{C}. \tag{1}$$

The matrices $\mathbf{M}$, $\mathbf{W}$, and $\mathbf{C}$ represent muscle activation, spatial pattern, and temporal pattern matrices, respectively. Matrix $\mathbf{M}$ consists of muscle activation vectors $\mathbf{m_i}$ ($i = 1, 2, \ldots, n$) to represent the activation of n different muscles (Eq. (2)).

$$\begin{aligned}\mathbf{M} &= \begin{pmatrix}\mathbf{m}_1(t) & \mathbf{m}_2(t) & \ldots & \mathbf{m}_n(t)\end{pmatrix}^{\mathrm{T}} \\ &= \begin{pmatrix} m_1(t_0) & \ldots & m_1(t_{\max}) \\ \vdots & \ddots & \vdots \\ m_n(t_0) & \ldots & m_n(t_{\max}) \end{pmatrix}.\end{aligned} \tag{2}$$

The components of the vector are $m_i(t)$ to represent the discrete i-th muscle activation at time t ($1 \leq t \leq t_{\max}$). Variable n represents the number of muscles. Spatial pattern $\mathbf{W}$ is used to represent the relative activation level of muscle. Variable N indicates the number of muscle synergies. Its column shows N different spatial pattern vectors $\mathbf{w}_j$ ($j = 1, 2, \ldots, N$). The vector $\mathbf{w}_j$ consists of w_{ij} that represents the relative activation level of muscle i included in j-th muscle synergy (Eq. (3)).

$$\begin{aligned}\mathbf{W} &= \begin{pmatrix}\mathbf{w}_1 & \mathbf{w}_2 & \ldots & \mathbf{w}_N\end{pmatrix} \\ &= \begin{pmatrix} w_{11} & \ldots & w_{1N} \\ \vdots & \ddots & \vdots \\ w_{n1} & \ldots & w_{nN} \end{pmatrix}.\end{aligned} \tag{3}$$

Temporal pattern $\mathbf{C}$ is used to indicate the time-varying weighting coefficient of N muscle synergies (Eq. (4)). Its row shows N different temporal pattern vectors $\mathbf{c}_j$ ($j = 1, 2, \ldots, N$), which indicate temporal pattern corresponded to the spatial pattern vectors $\mathbf{w}_j$. Its components are $c_j(t)$ that represent the weighting coefficient of j-th muscle synergy at time t.

$$\begin{aligned}\mathbf{C} &= \begin{pmatrix}\mathbf{c}_1(t) & \mathbf{c}_2(t) & \ldots & \mathbf{c}_N(t)\end{pmatrix}^{T} \\ &= \begin{pmatrix} c_1(t_0) & \ldots & c_1(t_{\max}) \\ \vdots & \ddots & \vdots \\ c_N(t_0) & \ldots & c_N(t_{\max}) \end{pmatrix}.\end{aligned} \tag{4}$$

Figure 1 shows an example of the muscle synergy model. Three muscle synergies composed of spatiotemporal patterns are used to express n muscle activation. Spatial patterns $\mathbf{w}_{1,2,3}$ show the contribution of each muscle in the related muscle synergy and temporal patterns $\mathbf{c}_{1,2,3}$ represent the timing activation. Spatial patterns are constant, but temporal patterns change according to motion time of STS movement. Muscle activation is generated from the linear spatiotemporal patterns of muscle synergies. In Fig. 1, muscle activation is shown in gray areas; contributions of muscle synergies 1, 2, and 3 to muscle activation are described in red, blue and green dashed lines, respectively. To calculate the elements of the matrices $\mathbf{W}$ and $\mathbf{C}$, the non-negative matrix factorization (NNMF) [19] was used. The muscle synergies were extracted from each trial of each subject.

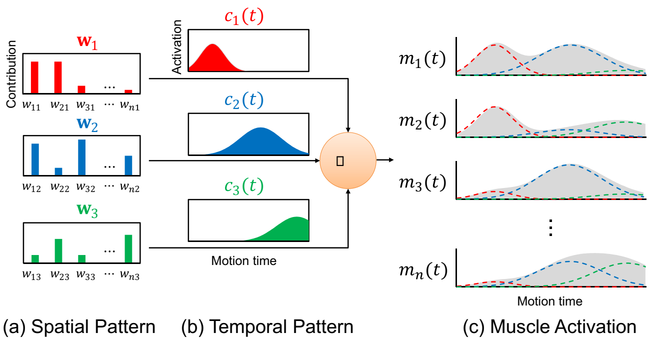


Fig. 1. Muscle synergy model. Spatial patterns $\mathbf{w}_{1,2,3}$ show the activation level of related muscles. Temporal patterns $\mathbf{c}_{1,2,3}$ represent the timing activation of related muscle synergies. The red, blue and green dashed lines represent the generated muscle activation from muscle synergies 1, 2 and 3 respectively.

TABLE I
PARTICIPANT DEMOGRAPHICS

	Mean ± SD (Range)
Post-stroke patients' group (n=33)	
Age (years)	58.1 ± 11.8 (34-79)
Lower extremity FMA score (out of 34)	23.8 ± 6.9 (9-34)
Gender (male/female)	23/10
Side affected (left/right)	23/10

B. Subjects

Thirty-three post-stroke patients, unable to perform STS independently participated in this experiment. These patients were asked to stand up from their own comfortable feet location. The average value of the lower extremity FMA score was 23.8±6.9 (see Table 1 for demographics information). Patients were divided into two groups based on the division by FMA scores: "mildly impaired" group (n=24, FMA $\geq$ 20) and "severely impaired" group (n=9, FMA $<$ 20). The patients performed STS with the interventions of PTs for 10 trials as the "Therapy" session (short-term rehabilitation).

PTs performed Bobath concept based neuro developmental therapy (NDT). They used their arms to assist the post-stroke patients and intervened on the thigh and pelvis of the affected side. Detailed intervention protocol can be found in our previous study [18]. The chair height was adjusted to the height of lower leg. The patients completed STS without moving their feet in all the trials. Informed consent of all participants was obtained, according to the protocol of the Institute Review Board of Morinomiya Hospital, Japan.

C. Analysis of Motor Recovery in Short-term Rehabilitation

This study used one motor impairment classifier developed by our previous study [11]. This classifier was able to evaluate the motor impairment of stroke patients using the temporal synergy features. The classifier was built using random forest (RF) algorithm and trained by the temporal synergy features of 24 mildly impaired and nine severely impaired post-stroke patients. These patients performed STS independently. This classifier could distinguish the mild and severe post-stroke patients based on temporal synergy features (test accuracy: 84.5±3.3%). The first aim of this study was to evaluate the motor impairment of patients in the "therapy" session. The evaluation was performed using the muscle activation data measured at the same time when the post-stroke patients performed STS with intervention. To achieve this aim, we used the model described above. The input features were the same 22 temporal features. The output was the trials classified as "mild" or "severe".

D. Experimental Setting

This experiment used a wireless surface EMG device (Cometa Corp.) to measure EMG data of fifteen muscles at 2,000 Hz. The same muscles of the affected side were measured [11]. The muscles were listed as follows: rectus abdominis, abdominal external oblique muscle, erector spine, gluteus maximus, gluteus medius, rectus femoris, vastus lateralis, vastus medialis, biceps femoris long head, semitendinosus, tibialis anterior, gastrocnemius lateralis, gastrocnemius medialis, peroneus longus, soleus. The EMG signals were firstly band-pass filtered (4th-order zero-lag Butterworth digital filter, passband 40-400 Hz) to attenuate DC offset and high-frequency noise [13][20][21]. Then the filtered signals were rectified and low-pass filtered (4th order, cut-off frequency 4 Hz) [13]. Each trial was cut from the whole recording EMG signals that started 1 second before the seat-off time until 2 or 3 seconds after the seat-off time. Some measured trials were deleted because of signal noises. The seat-off time was defined by the force data. Absolute motion time was used to represent the STS motion. To normalize the EMG data, the peak value of each muscle in each trial of the related participant was used for normalization [13].

The hip and feet reaction force data were measured by two force plates (TechGihan Corp.) at 2,000 Hz. The participant sat on one force plate, and placed their feet on the other. The force data was filtered with a low-pass filter at 20 Hz. It defined the seat-off time when the hip reaction force was less than 10 N.

The extraction of muscle synergies was performed in a Matlab environment (Matlab R2017a). For NNMF function, the algorithm was alternating least squares and the iteration was 100 as a default setting. We repeated NNMF function 50 times and selected the solution with the highest value of coefficient of determination.

E. Experimental Results of Evaluating STS with Intervention

We used the motor impairment model described in subsection C to evaluate the STS trials with interventions. The result showed that all the mild patients (trials) were mostly classified as mild. However, we found that an estimated half of the severe patients were classified into severe despite performing STS with intervention, as shown in Table 2. Therefore, we divided the severe patients into two groups. For those who were classified as "mild", it meant that these patients improved their motor function with

TABLE II
EVALUATION OF MOTOR IMPAIRMENT

Group	Label	Number of patients	Trials
Mild	Mild	24	221
	Severe	0	13
Severe	Mild (Improved)	5	45
	Severe (Non-improved)	4	38

PTs' intervention. Therefore, these patients were divided into the "improved" group and labeled as "improved". The severe impaired patients who were still classified as "severe" meant they did not improve from "severe" to the "mild" group. These severe patients were classified into the "non-improved" group. "Non-improved" means these patients did not improve from "severe" to "mild". These severe patients constructed the sub-group and were used to build the motor recovery of short-term rehabilitation model.

F. Experimental Results of Muscle Synergy Structure

For temporal patterns of muscle synergies, Fig 2 shows the averaged results of "improved" and "non-improved" groups respectively. Figure 3 also shows two subjects from "improved" and "non-improved" groups respectively. The example was used to represent the improvement during short-term rehabilitation and the difference between the two groups. The horizontal axis in the graphs shows absolute motion time of the STS motion, and the vertical axis shows the timing activation of the muscle synergy. The red and black lines represent the mean values of the temporal patterns in the "before" and "therapy" sessions respectively. For all the participants, muscle synergy 1 was first activated to bend the upper trunk. Then, muscle synergy 2 was activated to extend the knee and raise the hip. The two muscle synergies contribute to moving the body forward. Following this, muscle synergy 3 was activated to move the whole body upwards. Finally, muscle synergy 4 was activated to decelerate the horizontal movement of the CoM and maintain balance.

III. ESTIMATION OF MOTOR RECOVERY IN SHORT-TERM REHABILITATION

A. Subjects

In this section, nine "severely impaired" post-stroke patients (FMA $<$ 20) from the thirty-three post-stroke patients in section II were chosen. These patients were divided into "improved" and "non-improved" groups. They were asked to perform STS by themselves for 10 trials; this session was measured before the patients accepted the intervention and it was defined as the "before" session. The experimental setting was the same as in section II. The informed consent of all participants was also obtained, according to the protocol of the Institute Review Board of the Morinomiya Hospital, Japan.

B. Estimation Motor Recovery in Short-Term Rehabilitation

The second aim of this study was to identify features that could estimate the motor recovery of severe patients in short-term rehabilitation. The severe patients were divided into "improved" and "non-improved" groups in section II. We used their measured data without receiving interventions ("before" session) to train a new RF classifier. We chose data from the "before" session in order to estimate which type of severe patients could improve or not. The new RF classifier estimated which severe patients could improve from short-term rehabilitation. The gathered important features can be used as estimators for short-term rehabilitation and also provide information about new rehabilitation strategies.

C. Feature Selection

The feature selection method in temporal patterns of muscle synergies was the same as in our previous study [11]. Previous studies of post-stroke patients based on muscle synergy theory found that temporal patterns were merged in the locomotion of some post-stroke patients [13]. It was also suggested that post-stroke patients change their temporal patterns to achieve motion [20]. Thus, this study selected several representative temporal features to describe the temporal patterns of post-stroke patients. We chose start, end, peak and duration time of temporal patterns to represent the delayed or extended muscle synergy activation [20]. The overlap time between every two muscle synergies was also selected to describe the merged activation time [13]. The features were computed as follows.

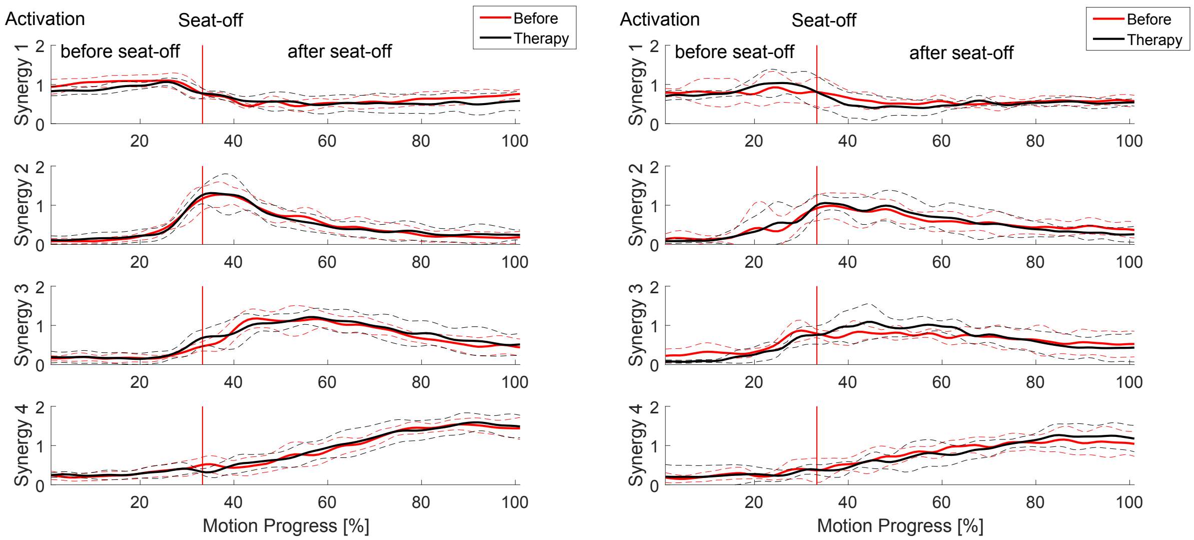
First, k-th muscle synergy was determined to be activated at time t when its activation $c_k(t)$ was above the mean activation $\bar{c}_k$. $\bar{c}_k$ was obtained from each trial of each subject using the following equation:

$$\bar{c}_k = \frac{\sum_{t_0}^{t_{\max}} c_k(t)}{t_{\max} - t_0}. \tag{5}$$

Then, other selected temporal features were obtained as follows:

1) Start time t_k^{st}: the first activated time of k-th muscle synergy.
2) End time t_k^{ed}: the last activated time of k-th muscle synergy.
3) Duration time t_k^{dur}: length between start time t_k^{st} and end time t_k^{ed}. It was obtained as follows: t_k^{dur} = t_k^{ed} - t_k^{st}.
4) Peak time t_k^{pk}: the time when the maximum muscle activation was achieved. It was obtained as follows: $t_k^{\mathrm{pk}} = \arg\max_t c_k(t)$.
5) Overlap time between every two muscle synergies k and l: $t_{k,l}^{\mathrm{ovlp}}$ = t_k^{ed} - t_l^{st}.

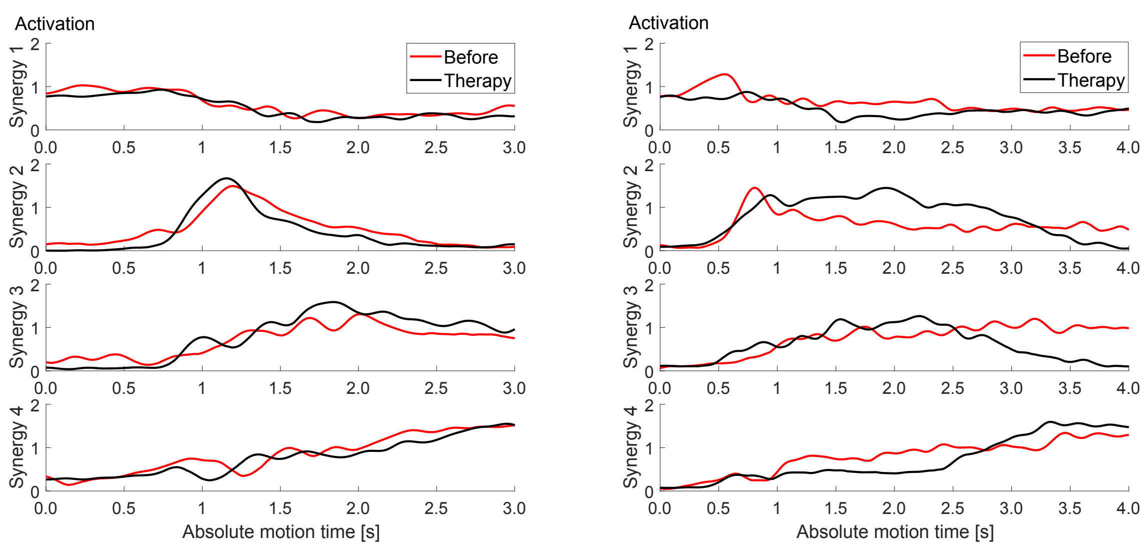
In our previous study, we found that peak, start and end time of synergies 2 and 4 could reflect the motor impairment of mild and severe patients [11]. We suggested that these synergy features might be important in motor recovery.



(a) Improved group

(b) Non-improved group

Fig. 2. Temporal patterns of four muscle synergies. The red and black solid lines represent the mean results of "before" and "therapy" sessions, respectively. The red and black dashed lines represent the standard deviation of "before" and "therapy" sessions, respectively. (a) Averaged results of the "improved" group. (b) Averaged results of the "non-improved" group.



(a) Improved group

(b) Non-improved group

Fig. 3. Temporal patterns of four muscle synergies. The red and black solid lines represent the average results of "before" and "therapy" sessions respectively. (a) One subject from "improved" group as an example. (b) One subject from "non-improved" group as an example.

Therefore, this study clarified the important features related to motor recovery during short-term rehabilitation.

D. Classification of Motor Recovery in Severe Post-Stroke Patients

The selected temporal features varied in post-stroke patients due to different motor impairment severities. To clarify which temporal features were important to estimate motor recovery in short-term rehabilitation, we used the RF classifier [22]. The RF classifier can multi-compare the importance of all the features, and sort the features based on their importance. The feature importance is computed using the mean decrease in the Gini index [22]. Furthermore, RF also provides a robust result to data-size.

This study used the RandomForest package in Rstudio and built the RF classifier with 500 decision trees as a default [23]. The RF classifier estimates if the severe patients recovered or stayed in the same stage. The input features were the selected 22 temporal features in the "before" session of severe patients. The RF classifier was trained based on these features and two labels ("improved" and "non-improved") in the dataset. 70% of the data was used as training data to train the RF classifier and 30% of the data was used to test the performance of the classifier. The data was randomly split a 100 times and the mean values of the training and testing accuracies were computed. After this, we retrained the RF classifier with the whole dataset and outputted the importance of features.

E. Results of RF Classifier of Motor Recovery in Short-term Rehabilitation

The new RF classifier was built to find the important features that could be used to estimate the motor recovery of short-term rehabilitation in severe post-stroke patients' STS motion. It was trained and tested with sub-group of post-stroke patients without receiving the interventions. In total, 22 features were selected as the input features for the classifier including the start, end, duration, and peak time of four muscle synergies and six overlap times between every two synergies. The training and testing accuracy were 85.5±3.7% and 85.6±5.3%.

The most important features were chosen based on the mean decrease of Gini impurity in predictions. Here we selected the top seven features from the importance of features. We verified that using these seven features to retrain the RF classifier could also obtain high accuracy (training accuracy: 86.6±3.6%, testing accuracy: 87.1±5.8%). The dataset consisted of the improved and non-improved groups, the main features that affected the STS performance were peak, start and end time of muscle synergy 3, peak, duration and end time of muscle synergy 4 and end time of muscle synergy 2, as shown in Table 3. Four features had significant differences between the two groups. Figure 4 shows the schematic diagrams of the change in these important features.

STS motion performed in the "non-improved" group was not classified as the "mild" although PT intervenes them, yet they might change some important features listed above. Hence we investigated the muscle synergy features of the "non-improved" group in both "before" and "therapy" sessions. We found that the start time of muscle synergy 3 was later in the "therapy" session. Additionally, end time of muscle synergy 2 was earlier and duration time of muscle synergy 4 was shorter. These phenomena was the same as "improved" group, and therefore 'non-improved" group showed improvement in these features. However, we found no adequate improvement in other remaining features in Table 3. These results indicated that "non-improved" group still improved activation time in some important temporal features for motor recovery in short-term rehabilitation.

IV. DISCUSSION

In this study, we analyzed abnormal muscle coordination based on muscle synergy and the synergy features that were able to estimate the motor recovery of post-stroke patients' STS in short-term rehabilitation. Previous studies have shown that high-intensity repetitive rehabilitation strategies can improve the STS performance; Langhorne reported that repetitive task training showed a significant improvement in STS ability [7]. However, these studies did not focus on the effects of abnormal muscle coordination caused by lesions in the central nervous system. To analyze the potential improvement of abnormal muscle coordination in post-stroke patients' STS during short-term rehabilitation, our study used a muscle synergy model and random forest classifier to estimate whether patients improved their STS with intervention.

Our previous machine learning model found that activation timing of hip rising (muscle synergy 2) was important to improve motor function [11]. We used this model to evaluate STS during short-term rehabilitation and we identified that some severely impaired patients did not improve motor function. These severe patients were divided into "improved" and "non-improved" groups. We then analyzed the differences between these two types of patients and discovered that muscle synergy 3 (body extension) was crucial. This finding suggests that severely impaired patients might require other interventions to improve the ability of body extension followed by hip rising training. We also found that the activation timing of muscle synergies 2 and 4 affects the motor recovery in short-term rehabilitation. These synergy activations could be trained by the present intervention. These findings also extended those STS studies reviewed by Boukadida et al. which investigated the effects of specific interventions on post-stroke patients and evaluated the effects based on clinical indexes or STS ability [8]. Our study investigated whether the neuro developmental therapy (NDT) intervention could improve the motor performance of STS in some post-stroke patients. As a result, we found that the patients could be divided into "improved" and "non-improved" groups. We then investigated the muscle synergy features between these two groups that could estimate the potential improvement of the NDT intervention. For the "improved" group, the intervention used in this study was suitable. However, for the "non-improved" group, it is reasonable to hypothesize that other rehabilitation strategies, such as training body extension abilities, may be more suitable. In addition, we suggest that different rehabilitation strategies could be applied to these patients that may improve their STS performance from short-term rehabilitation. To verify these hypotheses, prospective research studies are required.

Our results also provide compelling evidence for developing a new robotic training device or control strategies. Previous reviews for robotic device identified that there is insufficient evidence to use powered exoskeletons in clinical practice of post-stroke patients [9]. This study could classify the post-stroke patients into different levels and propose effective rehabilitation strategies required for each level. Therefore, this study provides information to robotic

TABLE III

IMPORTANCE OF FEATURES: IMPROVED AND NON-IMPROVED GROUPS

Feature	Decrease Gini	Improved (motion time [s])	Non-improved (motion time [s])	Difference from improved to non-improved	P-value
Peak of muscle synergy 3	4.39	0.68±0.45	0.71±1.04	Earlier	8.57E-01
End of muscle synergy 4	3.85	1.98±0.09	2.33±0.67	Earlier	2.04E-01
Start of muscle synergy 3	3.46	-0.08±0.34	-0.27±0.50	Later	4.78E-02
End of muscle synergy 2	3.06	1.08±0.47	1.71±0.82	Earlier	3.69E-05
End of muscle synergy 3	2.89	1.60±0.37	1.83±0.85	Earlier	1.00E-01
Duration of muscle synergy 4	2.28	1.40±0.23	1.60±0.46	Shorter	1.07E-03
Peak of muscle synergy 4	1.78	1.41±0.54	1.60±0.79	Earlier	1.60E-02
⋮	⋮	⋮	⋮	⋮	⋮

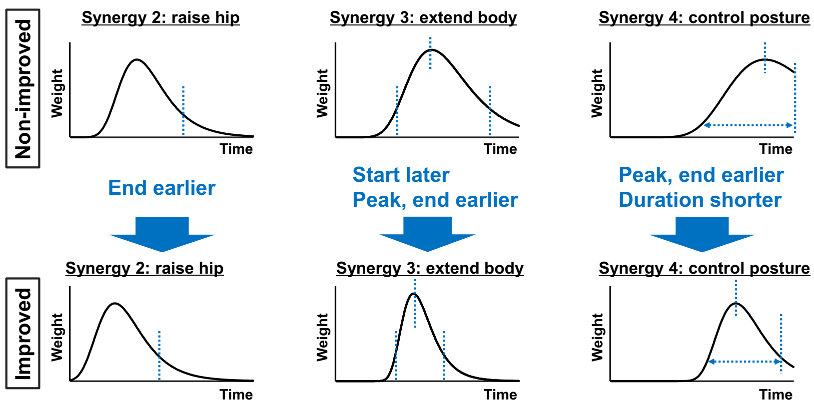


Fig. 4. Schematic diagrams of change in important features of muscle synergies 2, 3 and 4.

design or control strategies for different patients according to their needs. The specific design or control strategies aim at enhancement of body extension, training of posture control, or coordinate trunk and knee extension, which can be adapted to post-stroke patients who need the related rehabilitation strategy.

This study primarily evaluated the effects of the short-term rehabilitation in post-stroke patients. These patients stayed in the hospital for about six months and accepted daily rehabilitation to improve their motor abilities. However, the effects of long-term rehabilitation were not analyzed in this study. Prospective research about long-term rehabilitation is still required. In order to investigate the effects of long-term rehabilitation, it might be necessary to include the control group that received no intervention for comparison. In this study, we only recruited the patients in the sub-acute phase (less than 6 months after stroke) in the current study. The subacute phase is the period that the motor function of post-stroke patients is expected to recover better than the chronic phase (more than 6 months after stroke). It is difficult to have a control group in subacute patients for evaluating long-term effects. One possible way is conducting the experiment with chronic patients who do not have a chance to have inpatient rehabilitation. In this stage, it may be able to conduct two arm study including both intervention and control groups to evaluate the long-term effects.

We performed a targeted physical therapy for a specific movement, STS motion. However, the method used in this study could also be employed in other physical therapies for different movements. This assessment of the STS movement was based on synergy analysis. It could be generalized for the motor recovery of other movements like locomotion, posture control, etc. We would like to see more applications of this method in rehabilitation fields.

V. CONCLUSIONS

In this study, a random forest classifier was built to investigate the temporal muscle synergy features that primarily estimate the motor recovery in short-term rehabilitation. The muscle activation in post-stroke patients (n=33) was recorded and muscle synergies were extracted. First, this study evaluated the post-stroke patients performing STS with intervention of PTs and found that a part of the severely impaired patients improved their STS. Then, the temporal features of improved and non-improved patients were used to construct a new RF classifier. The important temporal features in muscle synergies 3 and 4 could estimate whether post-stroke patients could improve motor ability from short-term rehabilitation in STS. The muscle synergies 3 and 4 primarily contributed to body extension and posture control. The RF classifier showed that the temporal features of muscle synergy 3 primarily estimate the motor recovery of severe post-stroke patients in short-term rehabilitation. It also identified that the end duration and peak time of muscle synergy 4 reflect the recovery of STS performance in severe post-stroke patients. This result suggested that there was an appropriate order for training and we could evaluate the order based on muscle synergy. For some severe patients, we should train muscle synergy 3 prior to implementing the current therapy to train muscle synergy 2. For future work, the temporal features that reflect motor recovery of long-term rehabilitation will be investigated.

ACKNOWLEDGMENT

This work was supported by JSPS KAKENHI 26120005, 16H04293, and 18H01405.

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