Analysis of Human Standing-up Motion Based on Distributed Muscle Control

Qi AN[1], Yusuke IKEMOTO[2], Hajime ASAMA[1], and Tamio ARAI[1]

Abstract In developed countries, an aging society has become a serious issue; many activities of daily living (ADL) are impaired in the elderly. In order to improve this situation, it is necessary to develop an assisting method for the human standing-up motion because it is considered to be an important factor to ADL. It is unclear, however, how humans coordinate their multiple distributed actuators, muscles, due to the ill-posed problem of redundant their body system. In this paper, we analyze the human standing-up motion based on muscle coordinations, called synergies. A simulation method was developed to make mappings between muscle activations, joint torque, and the human body trajectory; thus, it can be predicted how modular muscle coordinations contribute to the motion. As a result, two primary synergies were extracted and how they coordinate to achieve the motion was elucidated; one synergy strongly affected joint movements and speed of the motion while bending the back and lifting the body up, and the other synergy controls their posture after they lift up their body. These findings could be useful for development of an assisting robotic system for rehabilitative training based on extracted distributed synergies from complex redundant human motion.

1 Introduction

In developed countries, a serious issue in healthcare is the aging society. As life expectancy increases, the ratio of the elderly to younger people has been increasing rapidly [1]. This situation has brought problems both to the elderly people and to caregivers. For the elderly, many activities of daily living (ADL) decline with age:

Qi AN, Hajime ASAMA, and Tamio ARAI
Dept. of Precision Engineering, Faculty of Engineering, The University of Tokyo, 7-3-1, Hongo, Bunkyou-ku, Tokyo, Japan, e-mail: anqi@robot.t.u-tokyo.ac.jp, asama@robot.t.u-tokyo.ac.jp, and arai-tamio@robot.t.u-tokyo.ac.jp

Yusuke Ikemoto
Dept. of Mechanical and Intellectual Systems Engineering, Faculty of Engineering, University of Toyama, 930-8555, Gofuku 3190, Toyama City, Japan e-mail: yikemoto@eng.u-toyama.ac.jp

walking, transferring themselves from the bed or chairs, dressing, and using the toilet [2]. Subsequently, many informal family caregivers suffer from physical and mental stress [3]. Therefore, in order to solve those problems, preventive medicine has become more and more important, with the suggestion that people should train themselves to stay healthy to avoid the necessity of being taken care of by others. For preventive medicine, human standing-up motion is considered to be an important factor; it is reported that elderly people without ability to perform this basic action have difficulty in mobility necessary for their ADL [4][5].

There have been studies to analyze human standing-up motion based on each joint angle or joint torque. For instance, according to changes of three joint angles (ankle, knee, and hip), Shenkman et al. divided human sit-to-stand motion into 4 phases: flexion momentum, momentum transfer, extension, and stabilization phases. They evaluated each phase in terms of momentum and stability [6]. On the other hand, Kotake et al. divided human sit-to-stand motion into six stages based on the angles of the ankle, knee, and hip, and computed the minimum torque of the hip and knee required to complete the motion [7]. It is unclear, however, how humans actually coordinate multiple distributed actuators, muscles, to achieve the standing-up motion. For assisting human daily motions, a robot suite has been proposed [8] to assist people using biological signals from their body, but suit-type machines need complex methods for controlling high D.O.F. state values due to redundant body systems. To avoid this complicated control, and to develop effective assisting machines, it is absolutely required to consider how human solves the ill-posed problem and to discover the dominant motion component of this human behavior.

We have focused on control of distributed muscle coordinations, called synergy, to analyze human standing-up motion [9]. Several researches suggest that training methods corresponding to muscles coordination are effective to improve motor control [10][11]; thus, it is important to analyze human standing-up motion based on synergies. If the standing-up motion can be divided into individual muscles movements that play different roles toward the motion, it will be useful to develop training or assisting methods. Our objective is, therefore, to extract essential synergies to control variant muscles in human standing-up motion. Moreover, a model of the motion is developed to simulate body trajectory from muscle activations in order to elucidate how each modular muscle synergy coordinates to achieve the motion.

2 Methods

2.1 Experiment Setup

2.1.1 Experiment Overview

In order to extract muscle coordination from human standing-up motion and to develop a simulation model, we performed an experiment to obtain three types of data during the standing-up motion. In this experiment, one healthy 22 years old healthy man participated and 12 trials were obtained.

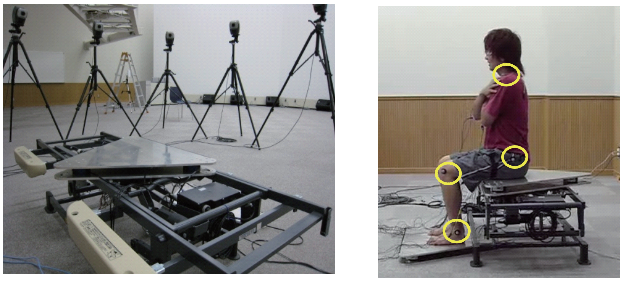
- Body motion trajectory
- Floor reaction force

- Surface electromyography (sEMG)

The experiment consisted of several trials of the standing-up motion, and at the beginning of trials, there were some initial conditions for body state of the subject: angle of his ankle was kept at 80 deg, his arms were crossed in front of the chest, and his back was straight. Also, the height of the chair used in the experiment was 0.425 m. Data recording of each trial continued for 7 secs and subject would start the motion approximately 2 secs after the start of recording by receiving a prompt from us.

2.1.2 Data Measurement

We recorded motion trajectory data at four points of the body using motion capture machines [HMK-200RT; MotionAnalysis]: ankle, knee, hip, and shoulder (Fig.1). The sampling rate for this data was 64 Hz and three joint angles, $\theta_{i\{i=foot,knee,hip\}}$, were obtained.



(a) (b)

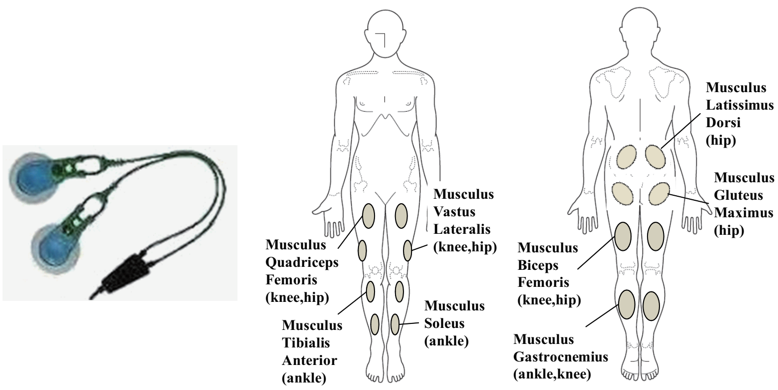
Fig. 1 (a) A motion capture machine with eight cameras [HMK-200RT; MotionAnalysis] was used in our experiment to record body position. (b) Four points were recorded during the experiments: ankle, knee, hip, and shoulder.

Reaction forces from both feet and hip were recorded at 64 Hz by two specially made force plates (Fig.2). There were three force sensors in each corner of the force plates, and the three vertical forces from one plate were summed up to calculate the reaction force.

Fig. 2 Two specially designed force plates placed at the positions of the feet and hip of subjects.

Personal-EMG[Oisaka Electroni Device Ldt] was used to record sEMG from sixteen muscles at 11200 Hz (illustrated in Fig.3-b). Two monopole electrodes (Fig.3-a) were attached along the axis of the muscle fibers, and distance between each electrodes were approximately 0.02 m. Muscle activation was recorded with single differential between two electrodes. The data were filtered with a 10 Hz hi-pass filter and 50-60 Hz hum noise filter. Moreover sEMG data were filtered by the smoothing filter calculated by eq.1 and downsampled to 64 Hz.

$$EMG_i(t) = \frac{\sum_{t'=0}^{24} EMG_i(t-t')}{25} \tag{1}$$



(a) (b)

Fig. 3 (a) Two sEMG monopolar electrode sensors were used to measure each muscle. (b) Sixteen muscles were measured (eight muscles for the each half body). Above figure illustrates positions of measured muscles and joints of muscle attachement.

2.2 Synergy Analysis

2.2.1 Movement Generation

Fig.4 illustrates relationship of inputs and outputs of human body systems to generate motion. When humans move, the brain sends motor commands into several muscles to exert forces of flexion or extension. Next, muscles generate torques related to differential of paired antagonist muscles attached to joints, and finally the human body moves according to its dynamics. In order to discover how distributed muscle coordination affects human body movement, we developed a simulation method was based on the model described in Fig.4.

2.2.2 Synergy Hypothesis

A synergy hypothes proposed by Bernstein suggests that human complex motion with redundant active degrees of freedom could be controlled by a relatively smaller number of degrees of freedom via coordinated activation of several muscles called synergy [12]. Furthermore, d'Avella et al. developed a synergy model that regards muscle patterns as a linear combination of several smaller patterns of muscles [13].

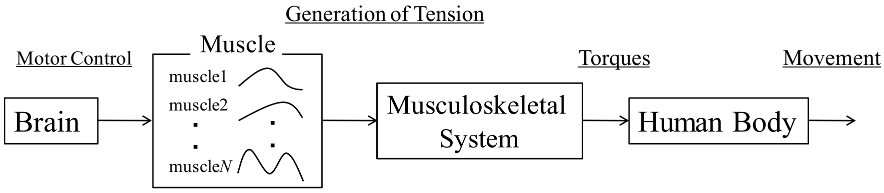


Fig. 4 The figure indicates model of human body movement. Firstly, brain sends motor control signals into muscles to exert forces by flexion or extension. Next, each muscle generates torque to human joints and human body moves according to its dynamics.

In this paper, we adopted this model to analyze the data. In the model, let d be the number of measured muscles, t_{max} be a maximum time steps of the obtained sEMG data and $\mathbf{m}(t)(d \times t_{max})$ be a matrix indicating activation of d muscles during the motion at time $t(0 < t < t_{max})$. This $\mathbf{m}(t)$ was approximated by the linear-summation of time-varying synergies $\mathbf{w}_i(t)_{i=1,2...N}$ (N is the total number of extracted synergies and the duration time of each synergy is not always the same as t_{max}) with non-negative coefficient c_i and onset time delay t_i as in eq.2. Although one pair of specific patterns is extracted from individual person, different motion can be achieved by changing values of c_i and t_i for every synergy. When changing c_i, strength of synergies activation can be controlled and the time of starting each synergy is adjusted by value of t_i.

$$\mathbf{m}(t) = \sum_{i=1}^{N} c_i \mathbf{w}_i(t - t_i) \tag{2}$$

2.2.3 Extraction of Synergies

We applied the decomposition algorithm [14] in order to extract synergies from observed sEMG patterns. This algorithm uses the multiplicative update rule to optimize elements of synergies, $\mathbf{w}_i(t)$, non-negative amplitude, c_i , and onset time delay t_i. Squared error E^2 was used to evaluate error between observed muscle patterns and generated patterns by the model.

$$E^2 = trace\Big((\mathbf{m}(t) - \sum_{i=1}^{N} c_i \mathbf{w}_i(t - t_i))^T (\mathbf{m}(t) - \sum_{i=1}^{N} c_i \mathbf{w}_i(t - t_i))\Big) \tag{3}$$

Also, the cross-validation method was used to determine the number of synergies to be extracted. The procedure is described as below.

1. The twelve trial of data were randomly divided into four groups (each group has three trials).
2. The number of extracted synergies was set.
3. Three groups (training group) out of four were used to extract synergies and the remaining group (testing group) was used to calculate E^2. This process was conducted four times to compute E^2 for all four data sets and to calculate R^2 by eq.4 where S_M^2 is variance of observed patterns.

$$R^2 = 1 - \frac{E^2}{S_M^2} \tag{4}$$

In the procedure, we calculated R^2 from obtained trials for the number of synergies, 1–5, in order to determine the minimum number of synergies to express human standing-up motion.

2.3 Simulation of Body Movement during Standing-up Motion

2.3.1 Link Model

The model with four links and three joints (described in Fig.5-a) was used to indicate human body. This model focused on planar movement of body; thus, body movements of right and left side were averaged together. From the experiment explained above, three joint angles, $\theta_{i\{i=foot,knee,hip\}}$, were obtained and every joint torque, $\tau_{i(i=\mathrm{ankle,knee,hip})}$, was computed by applying inverse dynamics calculation (eq. 5-7). In equations, m is mass of i-th link, g is gravity acceleration, $(x_n, y_n)_{n=1,2,3,4}$ is the position of center of gravity of each link, $(f_{xj}, f_{yj})_{j=2,3,4}$ is the horizontal force and vertical force between link i and link $i-1$, I is the inertial moment, and M is the moment from the center of gravity.

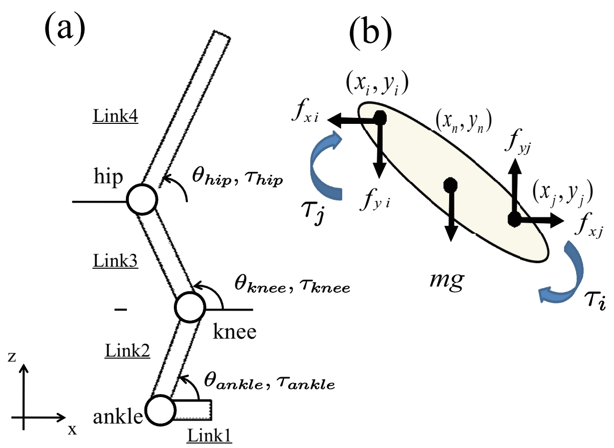


Fig. 5 (a) The link model used in our research to express human body. Each link expresses feet (Link1), lower legs (Link2), upper legs (Link3), and upper body (Link4) and joints between links are ankle, knee, and hip. (b) indicates variables used in computation of torques.

$$m\ddot{x}_n = f_{xj} - f_{xi} \tag{5}$$

$$m\ddot{y}_n = f_{yj} - f_{yi} - mg \tag{6}$$

$$I\ddot{\theta}_i = M - \tau_i - \tau_j \tag{7}$$

2.3.2 Estimation of Joint Torque and Angles

In order to understand how human body motion is generated from distributed muscle movements, neural networks were used to create mappings between sEMG patterns, and joint torques and between joint torques and angles (Fig.6) [15]. Both neural networks consist of three layers: input, hidden, and output. Among 7 secs recorded data, 3 secs were used for the analysis; the time when the shoulders of the subject reached the highest position was found in all trials, and 1 sec after that point and 2 secs before the point were used. All sEMG, torque, and angle data were normalized between 0.0-1.0 for the inputs and outputs of the neural networks.

One neural network was used to estimate one joint torque from sEMG patterns regarded as motor commands send by the brain. For the inputs of each neural network, only muscles attached to the joint were used; Fig.3-b illustrates which muscles are attached to each joint. There are two kinds of muscles: one-articular muscles and two-articular muscles; for example, musculus quadrcieps femoris was used for both knee and hip estimation. In addition to the strength of motor commands, both the length and the speed of muscle expansion and contraction are related to the tension generated by muscles [16]. Thus, in order to estimate joint torques, not only EMG patterns but also angle and angular velocity were included as inputs to the neural network, and a joint torque was obtained as an output signal. There were thirty-five nodes in the hidden layer of each network, and the back-propagating rule was adopted for the learning rule of neural networks. When learning phase of the neural network, angle data obtained from experiments and torque data calculated from previous session were used. In order to test the accuracy of the estimation, R^2 (eq.4) was used, where E^2 is squared error between obtained data and estimated data and S_M^2 is variance of the obtained data. When testing the accuracy, cross-validation method was used; observed trials of data were divided into nine sets of a training data, which were only used for teaching the network and the other three testing data which were used for calculating accuracy of the model. This was conducted four times to calculate R^2 for all trials.

Human joint angles were also estimated by a neural network. For input signals, three joint torques $\tau_i(t)$, joint angles $\theta_i(t)$, and joint angular velocity $\dot{\theta}_i(t)$ at time t were used (where i=foot, knee, and hip). Throughout forty nodes of the hidden layer, $\Delta\theta_i(t+1)$ and $\Delta\dot{\theta}_i(t+1)$ were obtained. For next inputs at time t+1, angle $\theta_i(t+1)$ and angular velocity $\dot{\theta}_i(t+1)$ were added by outputs $\Delta\theta_i(t+1)$ and $\Delta\dot{\theta}_i(t+1)$. Back-propagating rule was used for the learning rule, and in order to test the accuracy of the model, the same method for torque estimation was used here.

2.3.3 Detection of Synergy Contribution to Body Motion

In order to elucidate how extracted synergies affect human motion, the following procedure was repeatedly performed to simulate how the body trajectory changes corresponding to weakened sEMG patterns. For the simulation, both the torque and angle estimation neural networks previously described were used.

1. Weakened sEMG patterns were computed by decreasing c_i for the particular synergy in eq.2.
2. The torque estimation neural networks output changed torques from the originally learned data.
3. The angle estimation neural network received changed torques, and it outputted altered joint angles and angular velocities.

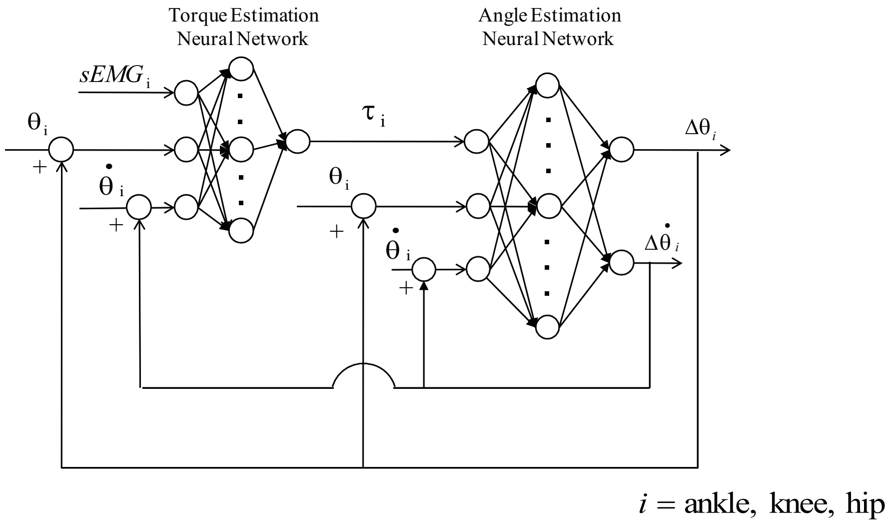


Fig. 6 The simulation method that estimates human body trajectory from muscle activations. Neural networks were used for both torque and angle estimations.

4. $\Delta\theta_i$ and $\Delta\dot{\theta}_i$ were recurrently added into inputs of both neural networks in order to obtain θ and $\dot{\theta}$ at the next time step.

3 Results

3.1 Results of Torque and Angle Estimation

Table.1 and Table.2 show the average value and standard deviation of R^2 of the proposed simulation model. Fig.7 indicates examples of both joint torque and angle estimations from one trial; blue solid line is observed data and red dotted line is estimated data. They indicates that neural networks can adequately construct generation of human body movement.

Table 1 Results of Torque Estimation

	Average R^2	Standard Deviation
Foot Torque	0.60	0.14
Knee Torque	0.80	0.12
Hip Torque	0.73	0.11

Table 2 Results of Angle Estimation

	Average R^2	Standard Deviation
Foot Angle	0.76	0.32
Knee Angle	0.94	0.15
Hip Angle	0.85	0.19

3.2 Results of Synergy Analysis

The synergy analysis and simulation method were applied to the data measured from one healthy 22 year old man. The number of synergies to be extracted from the observed EMG patterns is clarified by cross-validation. The relationship between mean value of R2 and the synergy number is depicted in Fig.7. It shows that two synergies are optimal to be extracted; before that number, the slope of the graph increases rapidly and the slope does not change sharply after that point.

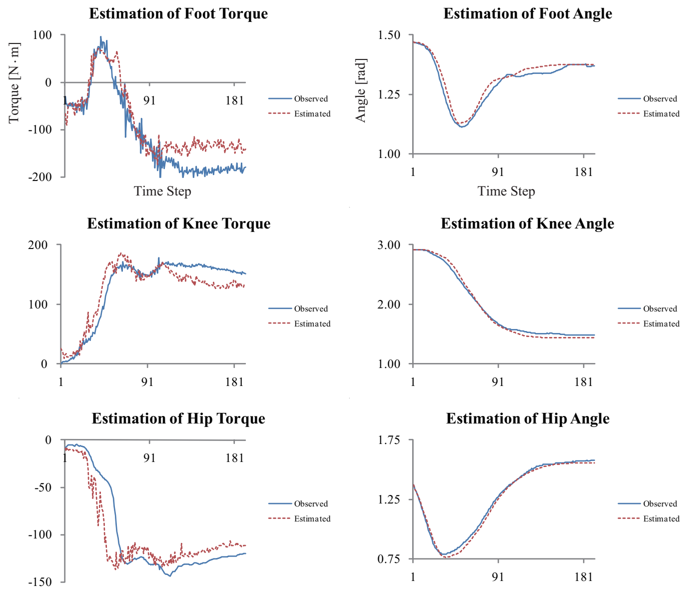


Fig. 7 Example of estimation of three joint torques and joint angles from the same trial. Left three graphs are results of torque extimation and right three graphs are ones of angle estimation. Blue solid line is observed data and red dotted line is estimated data.

As a result, two synergies were extracted (Fig.9) and Table.3 shows that synergy1 started at the beginning of the motion, and synergy2 started in the middle of the motion. In synergy1, all muscles except musculus gastrocnemius were activated, and in synergy2, musculus soleus, musculus gastrocnemius, musculus biceps femoris, musculus gluteus maximus, and musculus latissimus dorsi were activated.

Table 3 Results of the time delay for two extracted synergies.

	average time delay	standard deviation
Synergy 1	2.9	4.1
Synergy 2	88.2	1.8

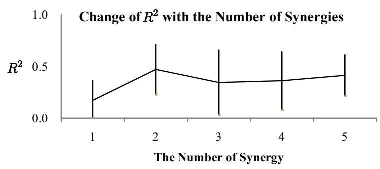


Fig. 8 Results of cross-validation method.

Changed joint angles corresponding to weakened synergies are shown in Fig.10. Each graph shows every joint angle when c_i of each synergy is changed to 100%, 70%, 40% and 10%. According to the Fig.10, when synergy1 was weakened, trajectory patterns of every angle were distorted and the timing of each angle changes was shifted backward; this means synergy1 works to lift the body upward. On the other hand, when synergy2 was weakened, angle change occurred only at the end of

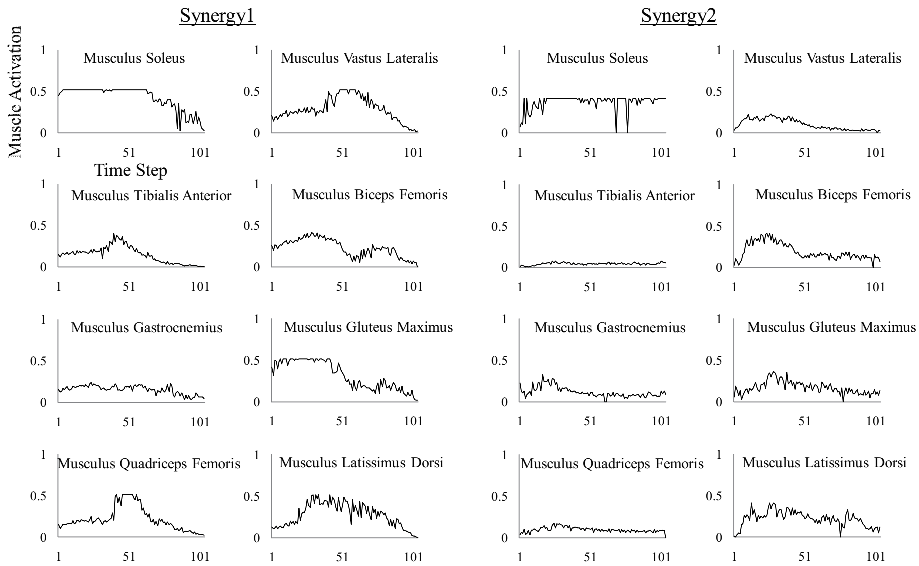


Fig. 9 shows extracted two synergies. From the decomposition algorithm, synergy1 started at the beginning of the motion and synergy2 started at the middle.

the motion; it means that synergy2 affected stabilization of their posture after lifting the body.

4 Discussion and Conclusion

Integrated simulation method to estimate human body trajectory from muscle activations was developed. This method consisted of two neural networks; one estimated a joint torque from sEMG patterns, joint angle, and angular velocity, and the other estimated changes of angle and angular velocity from joint torques, angles, and angular velocities.

From the results of synergy analysis, it was implied that human standing-up motion was dominated by two behaviors based on different muscle coordination corresponding to bending the back, and lifting up the body and to controlling posture after returning his back straight. Results of the angle change with weakened synergies show that when synergy1 was weakened, every angle changes rapidly and the timing of lifting up was shifted backward. This implies that when synergy1 was weakened, the subject would take more time to complete lifting up their body compared to when synergy1 was at the maximum level. When examining angles with weakened synergy2, only changes occurred at the end of the motion. Those differences show that synergy2 mainly affected keeping the posture stable.

Those findings from the analysis of the human standing-up motion can be used for controlling an assistive training machine. Fig.11 shows an example of controlling an assisting machine. Since the complex human standing-up motion can be divided into only two dominant synergies, ”a synergy controller” can compute necessary

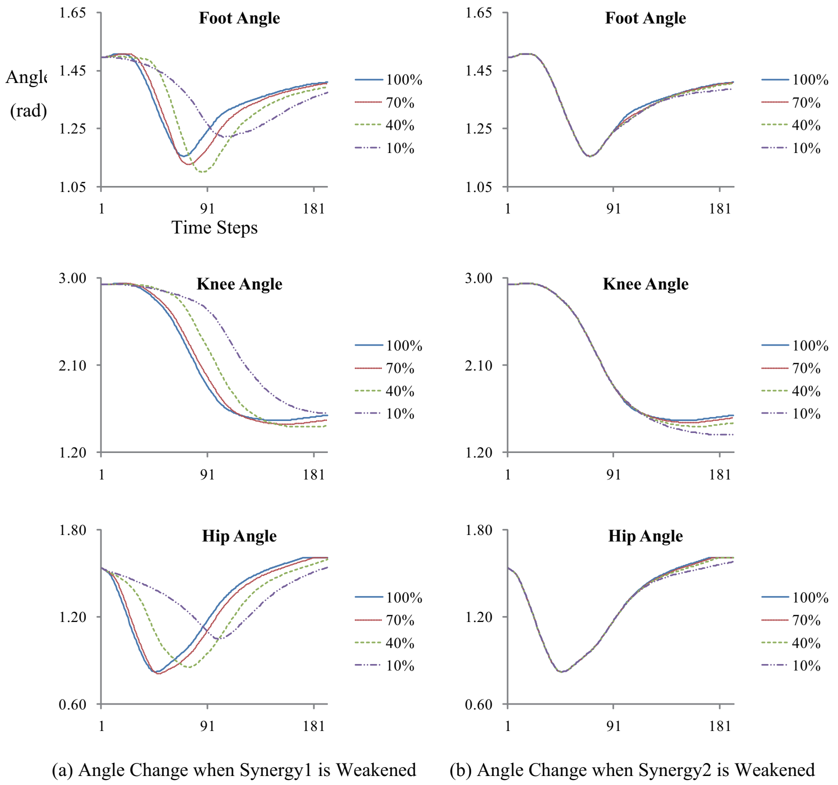


Fig. 10 Graphs indicate how each joint angle change with weakened synergies. Left three graphs show values when synergy1 was weakened, and right ones show values when synergy2 was weakened. X-axis represents a time step (1/64 sec) and y-axis represents angle (rad).

muscle activations from difference between desired and actual body trajectories. Then, the controller sends control signals to an assistive training machine to exert external forces to help people stand-up. However, the developed method was applied to only one subject in this research and it will be required to test the efficacy of the suggested method or synergy analysis although the model did not have a particular assumption for the subject.

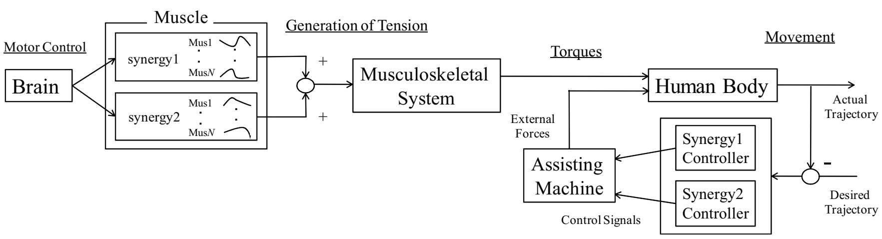


Fig. 11 Block diagram for controlling an assistive training equipment based on synergies.

Efficient simulation method for human standing-up motion was developed. Joint torques were estimated from sEMG data, joint angle, and angular velocity based on the mechanism of torque generation from muscles. Also, he human body trajectory was estimated by the output of neural network using joint torques, angles, and angular velocities.

To analyze the human standing-up motion in terms of distributed muscle coordination, two synergies were extracted. While one synergy started at the beginning of the standing-up motion, which mainly activated seven muscles, the other synergy started at the middle of the motion and five muscles were activated. Synergy1 controls the speed of joint angles or timing of the motion when bending and lifting up their body and, the other synergy mainly affected the posture of the body after lifting up the body. This finding would be helpful for development of an assistive training machine based on human distributed muscle coordinations.

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