# Extraction of Behavior Primitives in Human Standing-up Motion for Development of Power Assisting Machine

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Abstract—Recently, many older people have difficulty standing up despite that motion's importance in daily life. Therefore, a machine to support their standing-up motion is needed; yet we still do not know how people control their motor system when they stand up. For that reason, we can not produce such a machine. In this study, we analyze the system of people's standing-up motion using information related to muscle activity. Muscle synergy-coherent activations of groups of muscles are an efficient means to achieve this goal. The results of experiments demonstrate the importance of muscle synergies that exist when people stand up.

*Index Terms*—Electromyographic, Motor control, Torque estimation, Standing up

## I. INTRODUCTION

These days, the aging of society is advanced rapidly. Many old people have difficulty standing up. Standing-up motion is important because many actions rely on it. Therefore, machines to support those who cannot stand up are needed now.

To achieve this goal, we use synergy analysis to extract behavior primitives, which consist of standing-up motions. The idea of behavior primitives is efficient because it helps us to determine how people stand up: each primitive is expected to have a certain contribution to the motion.

In this study, we specifically examined the idea of muscle synergies: coherent activations of a group of muscles. We were able to divide the standing-up motion into several groups of muscle coordination. We also analyzed how each synergy contributes to the standing-up motion by building a musculoskeletal model with neural networks. To make this experiment meaningful, we obtained useful data based on electromyography (EMG), floor reaction force (FRF), and

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motion trajectory. These are all results of information technology development, which has improved the measurement equipment.

Through this study, we were able to understand the mechanism of human standing-up motion by extracting behavior primitives, such as muscle coordinate activations. In addition, we elucidated the contribution of each synergy to the human standing-up motion.

## II. BEHAVIOR PRIMITIVES

The system of moving properly or adaptively to the environment remains unknown. Here, we define "a behavior primitive" as a unit of the fundamental system to make up the whole motion. In other words, behavior primitives are components of human motion. In this study, we specifically examined standing up. We also extracted the behavior primitives. For discerning the behavior primitives, we analyzed muscle movement that occurs while standing up.

## A. Synergy hypothesis

The synergy hypothesis was suggested by Bernstein in 1967 [1]. Synergy is a group of several muscles performing a coordinated movement. We can observe various patterns of muscle activity using surface electromyography (EMG) during their motion. The synergy hypothesis suggests that those observed muscle activities can be divided into fundamental elements, called synergy. Actually, d'Avella's modeling of the synergy is efficient because their model suggests that muscle patterns can be generated as linear combinations of timevarying synergy, which are time-varying profiles of muscle activity. Each synergy has intensity and onset delay. We also use the sample regenerations of activity patterns of three different muscles to demonstrate its efficiency. In this sample, each activity uses three different muscles (Figs. 1a and 1b); each synergy consists of the same number of muscles.



Fig. 1. The longitudinal axis of each graph represents the muscle level activation; the horizontal axis shows time. Two time-varying synergies are scaled in amplitude  $(c_{i|\{i=1,2\}})$  and shifted in time  $(t_{i|\{i=1,2\}})$ . Then those two synergies are summed together to generate original muscle patterns

Synergies represent the time course of the activation level for each muscle. To generate the original muscle profiles, each synergy must be scaled in amplitude by a non-negative coefficient (c1 and c2); every synergy is shifted in time by an onset delay (t1 and t2). Then the elements of different synergies are summed together corresponding to the same muscle and same time. Therefore, even though each synergy has its own muscle profile, it can regenerate muscle patterns of various kinds by changing the amplitude and time delay [2]. Although d'Avella's model is simple, it is an efficient way to describe the synergy hypothesis in a quantitative manner. In this study, we define synergy as human behavior primitives and extract them.

#### B. Process of extracting behavior primitives

This section explains the flow of the extraction of behavior primitives. To find behavior primitives, we analyzed the human motion, standing up, from several perspectives. First, we must examine a command from the human brain. Although the brain sends a command to the body to stand up, it is difficult to observe that command stimulus in the brain accurately. Therefore, we used electromyography (EMG) to characterize the command from the brain. Thereby, we can see which muscle is active and when it is active. The command from the brain controls the muscle. This order is exactly what the synergy expresses; synergy is the muscles' activity level profile. It is a way for muscles to be active through movement. We extracted certain synergies from the human standing-up motion.

In addition, to characterize the function of synergies during the motion, we must determine which synergy plays what kind of role during their motion. To do so, it is necessary that we record the human movement, especially the trajectory of several parts of the body, and the torque of the human joint. Corresponding synergy directly to the human motion, such as trajectory and torque, the synergies' function can be found. The trajectory and torque can be visualized using certain apparatus.

The human system of muscles and bones, the musculoskeletal system, is complex because of the numerous muscles and bones that are present in the human body. This system is important because it connects human muscle activity to actual human movement. For this study, we construct neural networks to relate the functions of synergies to actual human movement.

#### III. METHOD AND EQUIPMENT A. Method for extraction of behavior primitives

We used a decomposition algorithm developed by d'Avella to extract the synergy from observed muscle patterns [3]. Additionally, we measured EMG patterns with one subject in an experiment. Also it is necessary to know the exact number of synergies from observed muscle patterns. We used cross-validation to check a sufficient number of patterns to determine the number.

1) Experiment 1: EMG signals: One healthy 22-year-old man participated in this study. In the first experiment, to analyze EMG signals while standing up, we record EMG signals from 10 muscles, as presented in Fig. 2. Those muscles are considered important muscles for standing-up motion from an anatomic viewpoint. During the standingup motion, from a sitting posture to a standing posture, the subject had his arms crossed in front of his chest. We also recorded the floor reflection force (FRF) at four places in the foot: right toe, left toe, right heel, and left heel. We used FRF as trigger signals; those signals gave signs for the EMG recording starting point. The EMG measurement machine recorded EMG patterns for 2.5 seconds before the time when FRF values exceed a certain threshold value to 2.5 seconds after that time. Therefore, we were able to obtain EMG patterns from the phase of sitting, which is the starting point of the motion, to the phase of standing, which is an end point of the motion. The EMG data were filtered with an upper cut-off frequency of 500 Hz and lower cut-off frequency of 200 Hz. Those data, EMG patterns and FRF patterns, were first sampled at 204.8 Hz. We obtained 18 samples from this experiment. In addition, we filtered those data using a smoothing filter and down-sampled these data sampling rates of 12.8. Therefore we obtain 64 values for one particular time series EMG profile. The EMG patterns we obtained from this experiment were 10 for one sample (five muscles for each half of the body), yet we regard the function of muscles obtained from each half body as equivalent. Therefore, we averaged two values of the EMG patterns from the same time and the same muscle of both the left half of the body and right half of the body. Two places to measure EMG patterns were used for the same muscle: the left half of the body and



Fig. 2. This figure shows EMG sensor locations; the gastrocnemius muscle, quadriceps femoris muscle, gluteus muscle, latissimus dorsi muscle, and the prevertebral muscle.

the right half of the body. Additionally, we normalized each muscle data as 0–1 using the benchmark in maximum muscle activity for all trials for the particular type of muscle.

2) *Decomposition Algorithm:* This algorithm developed by d'Avella has three parts [3].

Under the situation in which d muscles are observed, let *i*-th synergy  $w_i(t)$  be a vector representing activation of d muscles at a certain time t. Consequently, the *i*-th time-varying synergy can be written as  $\{w_i(t)\}_{i=1...n}$  (let n be the number of synergies to be extracted).

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

In that equation, m(t) represents the activity level of d muscles for time  $t(0 < t \le j)$  (let j be the total time step of the observed EMG patterns, and in our study j is 64 and d is 5), and m(t) is expressed as formation (1), where  $c_i$  is non-negative scaling coefficient for the *i*-th synergy and  $t_i$  is time-delay for the *i*-th synergy. Given a maximum total time length of synergy  $t_{max}$ , the *i*-th synergy  $W_i$  is a matrix which can be made of d rows and j columns. The *i*-th synergy's columns  $\{w_i(t)\}$  are d-dimensional vectors, which represent the activation of d muscles of *i*-th synergy at the k-th time  $t_k(0 < k \le j)$ .

$$\mathbf{w}^{i}(t_{k}) = \begin{cases} 0 & t_{k} < 0 \\ \mathbf{w}^{i}(t_{k}) & 0 \le t_{k} < t_{max} \\ 0 & t_{k} \ge t_{max} \end{cases}$$
(2)

This algorithm's object is to extract the time-varying synergies that minimize the total squared reconstruction error calculated by formation (3) on a set of *s*-th observed EMG patterns sample. This algorithm uses the multiplicative update rule for optimization of non-negative amplitude and elements of synergies to achieve this goal.

$$E^{2} = \operatorname{trace}\left(\left(\mathbf{M}_{s} - \mathbf{W}\mathbf{H}_{s}\right)^{\mathrm{T}}\left(\mathbf{M}_{s} - \mathbf{W}\mathbf{H}_{s}\right)\right) \qquad (3)$$

The time-series patterns of muscles can be regenerated through formation (4), where  $M_s$  (with d rows and j columns) is a matrix indicating the time-series EMG patterns. Matrix W (with d rows and  $n \times j$  columns) represents all n synergies set with the discrete time length of j.

$$\mathbf{M}_s = \mathbf{W} \mathbf{H}_s \tag{4}$$

$$\mathbf{H}_{s} = \begin{pmatrix} 0 & 0 & c_{1} & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & c_{1} \\ \hline \\ \hline \\ 0 & c_{n} & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & c_{n} & 0 \end{pmatrix}$$

Matrix  $H_s$  (with  $n \times j$  rows and j columns) has the function of scaling in amplitude and shifting time for the *s*-th synergies. In fact,  $H_s$  has n blocks, and for example, *i*-th block has information of the amplitude  $c_i$  and time delay  $td_{si}$  (the amplitude  $c_i$  starts at  $td_{si}$ -th column of the *i*-th block).

Step 1: For the s-th observed muscle patterns  $M_s$ , we calculate the time delay  $td_{si}$  for every *i*-th synergy  $W_i$  by formation (5). For each synergy, we adopt the best time delay  $td_{si}$ , which gives the maximum value of  $\psi_{si}(t_{si})$ .

$$\psi_{si}(T_{si}) = \sum_{t} \mathbf{m}_s(t)^{\mathrm{T}} \mathbf{w}_i(t - td_{si})$$
(5)

Step 2: Under the particular time delay  $td_{si}$ , calculated by Step 1, we renewed the value of non-negative amplitude  $c_i$ by formation (6). In addition,  $H_{si}^T$  is the matrix of *i*-th block, which is extracted from  $H_s$ . Furthermore,  $\bigcirc_{si}$  is the matrix which replaces the elements of  $H_s$  by 1.

$$c_{si}^{\text{new}} = c_{si} \left( \frac{\text{trace}(\mathbf{M}_s^T \mathbf{W}_i \odot_{si}[td_{si}])}{\text{trace}(\mathbf{H}_{si}^T \mathbf{W}_i^T \mathbf{W}_i \odot_{si}[td_{si}])} \right)$$
(6)

Step 3: Using the time delay  $\{td_{si}\}_{i=1...,n|s=i...,s}$  and  $\{c_{si}\}_{i=1...,n|s=i...,s}$ , we renewed W using the equation (7).

$$\mathbf{W}_{ij}^{\text{new}} = \mathbf{W}_{ij} \left( \frac{(\mathbf{M}\mathbf{H}^T)_{ij}}{(\mathbf{W}\mathbf{H}\mathbf{H}^T)_{ij}} \right)$$
(7)

(in formation (7)  $\mathbf{X}_{ij}$  represents the *i*-th row and *j*-th column element of the matrix X)

Repeat the process of stepI to stepII until the sum of squared errors  $E^2$  converges.

3) Cross-validation procedure: In this synergy model, the number of synergies to extract is an important issue. We must test the accuracy of the model to determine the number [4]. The accuracy of the model is related closely to the number of synergy: if it is smaller than the best fitted number, the model cannot explain the observed data sufficiently; if it is beyond the best number, it is also not good because the model extracts the specific model's noise. Therefore, it is important to try the model using different numbers. The cross-validation procedure is as follows.

First, we randomly divided 18 data into six groups; each group has three datasets. Then we chose five datasets as training data and one dataset as test data. Next, we calculated the model from the chosen five datasets using the decomposition algorithm, and computed the mean validation  $R^2$ 

from eq. (8) with the test dataset. Actually,  $E^2$  is the squared error calculated from (3);  $S_M^2$  is the variance of all observed EMG patterns. Repeat this process six times changing the test dataset to obtain the accuracy of each model which has different number to extract synergies. Doing this calculation for certain numbers, we obtained the specific number.

$$R^2 = 1 - \frac{E^2}{S_M^2}$$
(8)

## B. Method for building a musculoskeletal system

The human musculoskeletal system is so complex that it is not understood completely. However, a method of constructing a musculoskeletal system using neural networks was developed by Koike et al. [5]. This method is very sufficient to detect the human musculoskeletal system. We also apply neural networksto build that complex system and produce the function between EMG patterns and human movement during the standing-up motion.

1) Link model: We used a link model to represent the human body in this study. Because we specifically examined on the motion of human standing up, we need a four-link model with three joint parts. Each link indicates a particular human body part; between each link, one particular joint exists (Fig. 3-a). This four-link model is sufficient to portray human body movement during the standing-up motion. We apply some assumptions to use this model. First, every body segment, indicated by the "link" in this model, is rigid. The second is that every joint is uniaxial; body movement is expressible in the x-z plane. The third is that the human arms and head are included in the link4 that indicates the body trunk.

2) Experiment 2: Motion capture: We performed another experiment to monitor the movement of the human while standing up. We used a motion capture machine [HMK-200RT; MotionAnalysis] to record the positions of parts of the human body. The recorded parts are four points: acromion, greater trochanter, articulatio genus, and ankle. Positions of those regions are necessary because they are endpoints of each link explained above. In this experiment, the sampling rate was 64 Hz. When we used this for computation, we down-sampled this to the 12.8 Hz to adapt it to EMG pattern sampling rate. At the beginning of the standing-up motion, the subject kept the angle of his ankle at 80 deg. His back was straight; the chair height was 425 mm. Those conditions were the initial state of the subject. From this experiment, we obtain angle of each joint,  $\theta_{i\{i=ankle,knee,hip\}}$  shown in Fig. 3-(a).

3) Experiment 3: Calculating torque: We also monitored FRF using a forceplate. This measurement is for computing the torques of each joint in the motion. We consider the forces and torques to the body as shown in Fig. 3-(b), where m is the mass of the body represented using a link, g is gravity,  $(x_n, y_n)_{n=1,2,3,4}$  is the position of center of gravity of each link,  $f_{xi,xj}$  is the horizontal force of particular position,  $f_{yi,yj}$ 



Fig. 3. (a) This figure portrays the positions measured by the motion capture machine: the ankle, articulatio genus, greater trochanter, and acromion. (b) This shows parameters we defined to every link.

is the vertical force,  $\tau_{i,j\{i,j=ankle,knee,hip\}}$  is the torque of each joint, I is the inertia moment, and M is the moment from the center of gravity.

The equations of motion can be written as follows.

$$m\ddot{x}_n = f_{xj} - f_{xi} \tag{9}$$

$$m\ddot{y}_n = f_{yj} - f_{yi} - mg \tag{10}$$

$$I\ddot{\theta}_i = M - \tau_i - \tau_j \tag{11}$$

Those equations are approved to every link  $n_{\{n=1,2,3,4\}}$ . Therefore, we solved these equations for each torque by inverse calculation under the conditions of a link model.

4) Musculoskeletal system modeling: In this study, to see the functions of synergies, we must construct a certain musculoskeletal model to verify how every synergy works. For this study, we used neural networks to estimate the relationship between synergies and human movement. Koike has already developed that between EMG patterns and human arm torque and trajectory [5]. For this study, we used the same method to detect the musculoskeletal system. We first build neural networks that construct functions between the EMG patterns and joint torques. As input signals, we put the five EMG patterns regenerated from extracted synergies. Thoes patterns are 64 time series datas and they are liner sum of several synergies with the average amplitude and the average time-delay extracted from synergy analysis into it. As output signals, we obtained the three joint torques of the ankle, knee, and hip. We used backpropagation to renew the weight of this neural network. As teaching data, we used five EMG patterns for input data, and also used three calculated joints torques for output data. We designate this neural network as "NN1". We also used neural networks to determine the relationship among those human torques and human body trajectory. For this neural network, we used joint torques calculated by NN1, angles of each joint, and angle rates of each joint as input signals; as output data, we used angular accelerations of each joint. To train those networks, we used backpropagation as well. The difference from the former network is the recurrent part. As shown in Fig.4, this neural network has the output signal, angular acceleration, back to input signals as recurrent factors. Therefore, we



Fig. 4. The structure of neural networks for estimation of the torque and angular acceleration for each joint



Fig. 5. The graph slope reaches a peak at 3; it indicates that the number is sufficient and saturated to explain the motion of standing up.

were able to estimate the position of the body repeatedly by computing the angular acceleration. This neural network is designated as "NN2".

# IV. SYNERGY ANALYSIS

The number of synergies to be extracted from the observed EMG patterns was clarified by cross-validation. The relationship between mean validation  $R^2$  and the synergy number is depicted in Fig. 5. Specifically regarding synergy number 3, it is a sufficient number: before that number, the slope of the graph increases rapidly; after that point, the slope does not change sharply. The salient implication is that three synergies are sufficient for reconstruction of the observed EMG patterns: adding more synergies would merely increase redundancy. Therefore, we determined the synergy number to extract as three.

We used the decomposition algorithm again to determine synergies. The squared error  $E^2$  converged; the patterns for the synergies are portrayed in Fig. 6.

From these figures and Table 1, we were able to presume the function of each synergy. Synergy 1 is started in no time-delay (Table 1); the gastrocnemius muscle activity is prominent. This synergy starts at an early time, and controls the ankle joint. Controlling the ankle is important because it is a point of support for the upper part of the body. Therefore, this synergy is presumed to have the function of controlling the posture of the human body at the beginning of the standing-up motion. This starts earlier even than the movement, such as bending and lifting the upper body.

Synergy 2 is similar to the first synergy. In this synergy, the gastrocnemius muscle activity is also prominent. However, unlike the first, this synergy starts at the latest point among

TABLE I This represents the time delay factor t for every synergy.



Fig. 6. These graphs show the synergy we extracted. Each synergy has its own characteristic. X-axis represents each time step of synergy. Y-axis represents the muscle activity for each muscle and these values are normalized of 0-1.

the three synergies. Therefore, this synergy can be thought to have the function of controlling the posture of the human body at the final stage of the motion.

Synergy 3 differs from the rest with respect to the number of the active muscles. Every muscle is active in this synergy compared to the others. Moreover, this synergy starts at middle of the motion, which is remarkable because the dynamic movement of body starts at this point. Therefore, this synergy can be considered to have the function of producing movement, such as bending the back and lifting the upper body.

#### V. BUILDING OF THE MUSCULOSKELETAL SYSTEM

We were able to estimate the torques of three joints sufficiently. The neural networks for estimating angular acceleration also converged. Therefore, when we have torques calculated by NN1 with all three synergies, the regenerated movement by NN2 is reconstructed similarly to the originally measured one. Then, we examined and simulated the function of synergies by shutting out one synergy. For example, to check the function of synergy 1, we arranged input signals, EMG patterns, of NN1 being made only from synergy 2 and synergy 3. In results, the output signal from NN1, torques of three joints, lacked information of synergy 1, thereby putting that output into one input signal of NN2, we were able to see how the standing movement changed. Similarly, we checked all the functions. Those ways of standing up differs from the way determined using all synergy input. Time series data of



Fig. 7. Simulation results. The graphs portray the angles of ankle, knee, and hip with different conditions.

each angle of the joint change dramatically, as in the Fig. 7.

The angle of the ankle without synergy 1 differs greatly from others at the early stage of the motion. Consequently, this synergy controls the ankle movement of the early time. This function is the controlling posture for compensating the movement, bending the upper body, coming immediately after synergy 1.

The angle of the ankle without synergy 2 also differs from that with all synergies in the late stage of the motion. This change also indicates that synergy 2 is the one controlling the ankle movement. This function is for posture control as well. However, the aim differs from that of synergy 1. Synergy 2's posture control is useful for accommodating the change of center of gravity by lifting the upper body. This movement is rather large throughout the entire motion of standing up. Therefore, controlling the posture is also necessary.

Without synergy 3 the angles of the ankle, knee, and hip all depart from normal values at the middle of the time when people lift their body. This result suggests that people without synergy 3 lose control of three angles of joints from the time they lift their body.

#### VI. RESULTS

We were able to extract three synergies from the motion of standing up; these are clearly human behavior primitives. Additionally, we found that each synergy has its own original function for standing up. There seem to be two prominent types of synergy: one for making dynamic movements and one for posture control. Both functions are necessary for standing up. The function for dynamic movement is necessary because standing up is a dynamic motion. Standing up is a radical change of the human body state because, at first, the human sits on a chair. This phase is very stable because it has support for the person's weight. However, once beginning standing up, the body state changes rapidly from a stable state to an unstable state. People must bend and lift their upper body: this movement is dynamic. Synergy 3 has exactly this function. Synergy analysis showed that every muscle involved in synergy 3 is active. Furthermore, the simulation through musculoskeletal system built by neural networks suggests that the standing without synergy 3, every angle of joints is caused aberrant from the time they presumed to lift their body. On the other hand, synergy 1 and synergy 2 show a different function controlling the human body posture. The difference between those two synergies is the start time. Synergy 1 starts at beginning of the motion, which compensates the coming motion of bending the body. Synergy 2 is for accommodating the change of human body central of gravity caused by lifting the body. In both synergies, the gastrocnemius muscle is active. The simulation suggests that this activity is related to the ankle angle.

Therefore, through two analyses, we were able to find human behavior primitives during standing-up motion. Three synergies are involved. Each synergy has a clear function such as movement control and posture control.

## VII. DISCUSSION AND FUTURE WORKS

Each synergy has a clear function is important to produce a strong model for analyzing the standing-up motion. It can be readily inferred that people who have difficulty in standing up are expected to have some critical change in their EMG patterns. Therefore, if we can detect a problem by which a person can not stand up because of lack of synergy 3, which controls rapid movement, that knowledge is expected to be helpful to produce a machine to support their standing up.

In our future research, we will test these experiments using more subjects and confirm the function of synergies extracted from different subject. Additionally, we will build a better musculoskeletal system. Although we obtained clear results from the simulation, the model might have redundancy because of neural network characteristics: excessive and unnecessary connections are formed between inputs and outputs. Efforts to reduce the redundancy of neural networks might be needed to produce a more sophisticated model.

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