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A Neuromuscular Locomotion Controller that Realizes Human-like Responses to Unexpected Disturbances

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Abstract— **In this paper, we demonstrate that a neuromuscular controller built based on the human anatomical structure and motion data can realize human-like responses to unexpected disturbances during locomotion. This particular work concerns the response to trips due to obstacles and shows that the two strategies identified in biomechanics emerge from a single controller. We first identify the parameters of a neuromuscular network model using the muscle tension data during a human walking motion. The anatomically-correct network models the somatosensory reflex of the human neuromuscular system. We use this network as the controller for a musculoskeletal human model to simulate its response to disturbances. Simulation results show that our neuromuscular controller automatically results in the appropriate trip recovery strategy with a single set of parameters, although we do not explicitly model the trip response or the condition to invoke each strategy. This result implies that an appropriately designed locomotion controller can also provide rapid responses to trips without deliberate controller selection or planning.**

I. Introduction

Responding to unexpected disturbances is critical to biped robots standing and walking in uncontrolled environments, and a number of controllers have been developed for recovering balance from various types of disturbances such as external forces and uncertainty in the environment. Most work involves controller selection or motion replanning according to the state change caused by disturbances. In human motions, on the other hand, initial responses to disturbances take place before the sensory feedback involving the cerebellum can occur considering the signal transmission delay in the human nerve system [1]. Therefore, we can speculate that at least the initial response happens using the same controller as the normal behavior.

Tripping due to obstacles is one of the disturbances that requires rapid response for recovery but has been much less studied in robotics. According to the biomechanics literature [2], humans take one of the two strategies to prevent falling after trips, i.e., elevating and lowering strategies, depending on whether the trip occurred near the liftoff or the touchdown of the swing leg. The response is clearly involuntary because it can be observed in less than 100 ms after the trip, which is shorter than the time required to perform any voluntary feedback control using the cerebellum.

In this paper, we apply our earlier work on neuromuscular network model [3], [4], [5] to simulate disturbance response, with focus on balance recovery from trips. The model is an anatomically-correct neural network that represents the human somatosensory reflex loop with time delay. Taking the muscle lengths and tensions as inputs, the model outputs the muscle activities at the next time step. We can identify the model parameters using muscle length and tension data computed using inverse kinematics and dynamics algorithms for musculoskeletal human models [5]. In our previous work [4], we demonstrated that the model can successfully reproduce the knee jerk behavior in patellar tendon reflex.

We use a neuromuscular network model as the controller for a musculoskeletal model to simulate its behavior after trips. Although the model is identified only from a walking motion and is able to reproduce a walking motion when there is no disturbance, the two strategies for balance recovery after trips emerge from the same controller. This result implies that an appropriately designed locomotion controller can also provide rapid responses to trips without deliberate controller selection or motion replanning. In robotics, this approach will lead to more robust control of biped robots because a locomotion controller can quickly react to disturbances before controller switching or motion replanning takes place.

The result also serves as a partial verification of our neuromuscular network model. While our previous verification using patellar tendon reflex [4] only involved a single reflex loop, locomotion and tripping are more complex behaviors that involve the coordination of multiple muscles and reflex loops.

The rest of this paper is organized as follows. In Section II, we review related work on balance recovery for biped robots. In Section III, we summarize our neuromuscular network model and the method for identifying its parameters. Section IV introduces the human trip response studied in the biomechanics field and our method for simulating the response using our neuromuscular network model. We present the simulation results in Section V, followed by the concluding remarks in Section VI.

II. Related Work

Among a number of possible disturbances, balance recovery under external forces has been relatively well studied. Sugihara et al. [6] described a method for recovering balance by modifying the center of mass trajectory. Kudoh et al. [7] formulated an optimization problem for generating balance recovery behaviors in response to external forces. The work was subsequently extended to include stepping behavior [8]. Yamamoto et al. [9] proposed to plan steps based on the criterion that maximizes the set of initial states that a controller can bring to a statically stable pose. Atkeson et al. [10] showed that a single controller can exhibit multiple strategies for balancing. Stephens et al. [11], [12]

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also developed controllers for recovering from large external forces or unexpected loads.

Some work deals with external forces during locomotion. Huang et al. [13] used a set of fast online controllers along with offline pattern generation to handle disturbances. Komura et al. [14] developed a controller to absorb the angular momentum generated by external forces by changing the foot placement.

Another possible source of disturbance is uncertainty in the environment. Nishiwaki et al. [15] developed a framework for locomotion control where the gait is replanned based on the estimated posture that may be different from the planned one due to irregular terrains.

All of the above work requires a controller that has to be invoked when disturbances occur, or a set of controllers that should be designed in advance by modeling specific balance recovery behaviors. Our controller, on the other hand, is built and identified based on human anatomical model and walking motions without any reference to the human tripping behavior.

Compared to the disturbances mentioned above, responding to trips due to obstacles is less studied. In biomechanics, researchers analyzed the human tripping behavior and identified the two strategies to avoid the obstacle and recover balance [2]. However, the only work we are aware of that simulates trip response is by Shiratori et al. [16], where dedicated controllers for the elevating and lowering strategies are designed using finite state machines.

III. Neuromusculoskeletal Model

The neuromusculoskeletal model used in this work (Fig. 1) is a simplified version of the model presented in [5]. The model consists of the following elements:

1) The *skeleton* is simplified to a planar model in the sagittal plane with one rotational joint for each of the hip, knee and ankle joints.
2) Accordingly, we only consider the major *muscles* relevant to the flexion/extension movements of these active joints. This simplification leaves us 7 muscles for each leg: Hamstrings (HAMS), Gluteus Maximus (GLU), Tibialis Anterior (TA), Gastrocnemius (GAS), Rectus Femoris (RF), Vastus Lateralis (VAS), and Soleus (SOL).
3) Each muscle is associated with a *physiological muscle model* [17], [18] that relates the muscle tension with the muscle activity, length, and its velocity by

$$f_i = -a_i F_l(l_i) F_v(\dot{l}_i) F_{max,i}, \tag{1}$$

where f_i, a_i, l_i, $\dot{l}_i$, $F_{max,i}$ represent the tension, activity, length, velocity, and maximum voluntary force of i-th muscle, and $F_l(*)$ and $F_v(*)$ are the functions that represent length-tension and velocity-tension relationship respectively.
4) A *proprioceptive receptor model* [19], [20] is used to emulate the sensory information of the muscle spindles that detect the muscle length and its velocity, and the Golgi tendon organs that detect the muscle tension.

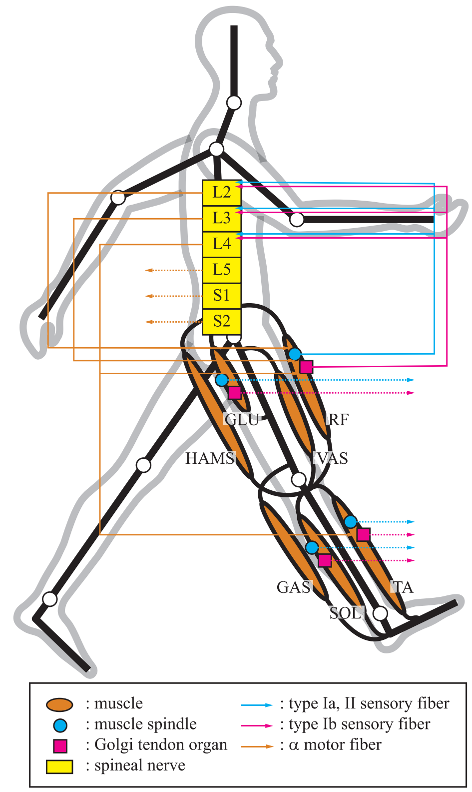

Fig. 1. The neuromusculoskeletal system. This system consists of the musculoskeletal model, physiological muscle model, proprioceptive receptor model, and neuromuscular network model. Only representative fibers and receptors are drawn.

TABLE I

Length in meters of the nerve between each pair of muscle and vertebra. — represents no connection.

muscles	L2	L3	L4	L5	S1	S2
HAMS	—	—	—	0.57	0.56	0.55
GLU	—	—	—	0.49	0.48	0.47
TA	—	—	1.08	1.06	1.05	—
GAS	—	—	—	—	1.13	1.10
RF	0.57	0.55	0.53	—	—	—
VAS	0.68	0.65	0.64	—	—	—
SOL	—	—	—	—	1.28	1.25

5) We build a *neuromuscular network model* [5] of the anatomically-correct neuronal binding among the muscles, proprioceptive receptors, and the spinal nerves [21], [22]. The model is a neural network with time delay for nerve signal transmission. Among the 31 vertebral columns, L2–L5, S1 and S2 are relevant to the muscles in our model. TABLE I summarizes the length of the nerve between each pair of muscle and vertebra if there exists a connection.

The weight parameters of the neurons in the neuromuscular network model are unknown. The parameters can be identified using any human motion data by the following process:

1) Compute the muscle length and tension by inverse

kinematics and dynamics [23], [24]. Also obtain the time derivative of the muscle lengths.
2) Convert the muscle tension to muscle activity using the physiological muscle model. Then compute the proprioceptive information using the proprioceptive receptor model.
3) Apply the standard back-propagation algorithm [25] to optimize the weight parameters.

IV. Simulating the Human Trip Response

A. Human Trip Response

According to studies in biomechanics [2], [26], humans take one of the following two strategies to recover balance after trips:

1) Elevating strategy: If the trip happened at the early stage of the swing (5–25% of the swing phase), the swing leg is lifted by the activation of Biceps Femoris that occurs 64 ms after the trip, resulting in an obstacle avoidance behavior.
2) Lowering strategy: If the trip happened later in the swing (55–75% of the swing phase), the swing foot is lowered by the activation of Rectus Femoris and Soleus that occurs 50–100 ms after the trip. These muscle activations result in an immediate contact of the swing leg with the ground.

Either strategy may appear when the trip happened in the middle of the swing.

As shown here, the initial response appears as a change in the muscle tension pattern as early as 50 ms after the trip, which is much faster than any voluntary feedback involving the cerebellum. Therefore, it would be reasonable to assume that no voluntary controller switching or planning occurs after a trip, and a locomotion controller that has been used to generate the walking motion should be able to produce the trip response.

B. Simulation with the Neuromuscular Network Model

We take the advantage of the biomechanics knowledge and investigate if our neuromuscular network model can reproduce these strategies even if the model parameters are learned only from locomotion data. We are particularly interested in the muscle tensions and swing leg behavior during the period from 0 to 100 ms after the trip. If the trip response strategies do emerge from a single controller, it suggests that an appropriate locomotion controller may be able to rapidly respond to trips, allowing enough time for other controllers or replanning algorithms to take over and thus realizing more robust locomotion control.

A successful reproduction of trip responses will also serve as another validation of our neuromuscular model. In contrast to the patellar tendon reflex used in the previous validation that only involves a single reflex loop [4], walking and trip response require the coordination of leg muscles.

We use the musculoskeletal model described in Section III for the simulation and place an obstacle on the walk path so that a trip occurs at a desired time. Before the trip, we assume that a walking motion sequence is replayed and compute the inverse dynamics to estimate the muscle tensions [23], [24].

When the swing leg hits the obstacle, we start the dynamics simulation using a dynamics simulator for humanoid robots [27]. We use the neuromuscular network model as the controller to obtain the joint torques of the skeleton model. The neuromuscular network first computes the muscle activities at time t from the state of the musculoskeletal model at time $t - t_d$ where t_d is the nerve signal transmission delay determined from the length of the nerves. The muscle activities are then converted to muscle tensions using a physiological muscle model [17], [18] and the current muscle lengths and their velocities. Finally, joint torques are computed from the muscle tensions using the Jacobian matrix of muscle length with respect to the joint angles [23]. The joint accelerations computed by the simulator are integrated to obtain the state at the next time step.

In addition to the muscles shown in Fig. 1, we also add several other elements to account for the elements unmodeled in the musculoskeletal model. Each joint in the upper body and arms is actuated by a proportional-derivative (PD) controller. Each of the knee joints receives additional spring-damper torque when the joint angle approaches the joint limit. A pair of weak spring and damper is attached to each ankle joint to model the passive elements around the joint because the passive torque has strong effect on the joint motion due to the small mass and inertia.

V. Experimental Results

A. Identification of the Neuromuscular Network Model

The walking motion sequence for the identification is captured by a commercial marker-based optical motion capture system with 16 cameras (resolution: 1280×1024 pixels, frame rate: 120 fps). The subject wears 52 markers whose locations are determined based on an improved version of Helen Hayes Hospital marker set [28]. In the neural network training [25], we used 0.01 for the learning rate, 0.001 for the forgetting rate, and 1000 for the number of iterations.

Figure 2 shows the result of the training, where the muscle activity obtained by inverse dynamics computation is shown in blue dotted line and the output of the network model is shown in red solid line for each of the left leg muscles. The vertical axis represents the muscle activity. The maximum error is 36%, the average error is 2.0%, and the variance is 3.7×10^{-6}. As shown in the graphs, the neuromuscular network model can precisely reproduce the muscle activity patterns, except for occasional peaks in some muscles such as Gluteus Maximus and Gastrocnemius.

We also verify the learned model by simulating one walk step resulting from the muscle tensions computed by the neuromuscular network model. The simulation result is shown in the bottom row of Fig. 3 along with the posture in the original motion capture data in the top row. We do not expect precise reproduction of the original walking motion because no reference trajectory is used. The contact condition would also be different from the original motion capture data because the simulation uses the bone geometry, while

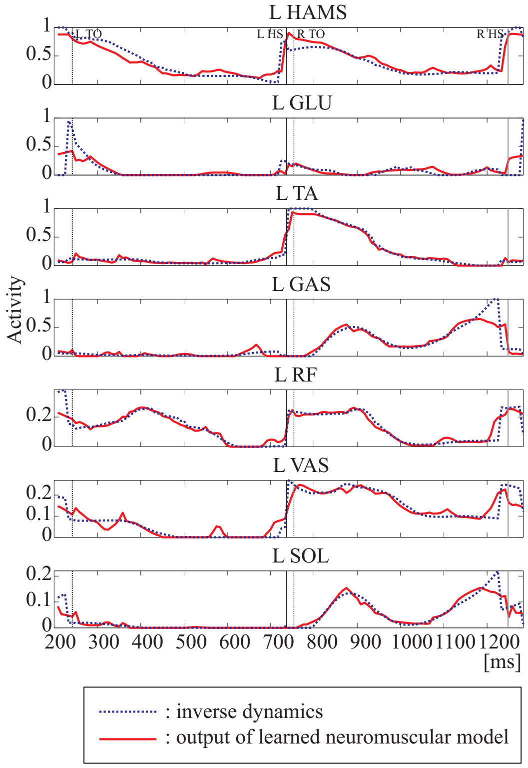

Fig. 2. The muscle activity during the walking motion. Red solid line: the output of the identified neuromusculoskeletal system, blue dotted line: the muscle activity from the dynamics computation and optimization. Black vertical solid line: L HS (left heel strike), black vertical dashed line: L TO (left toe off), gray vertical solid line: R HS (right heel strike), gray vertical dashed line: R TO (right toe off).

the motion is captured with shoes. However, the simulated motion is reasonably close to the original data.

B. Simulation of Trip Response

We simulate two cases of trip response separately. All timestamps in the text and figures are common starting from the beginning of the motion capture sequence.

In CASE 1, we place the obstacle so that a trip occurs at 13% of the swing phase (timestamp 308 ms) of the left leg, which should trigger the elevating strategy. In CASE 2, the trip occurs at 56% of the swing phase (timestamp 515 ms), which should trigger the lowering strategy. Figure 4 depicts several snapshots from the simulations, where the top and bottom rows show the results of CASE 1 and CASE 2 respectively.

Figure 5 shows the muscle tensions exerted by the neuromuscular network model in each case. The graphs show the muscle tensions in CASE 1 and CASE 2 with red and green lines respectively, as well as the muscle tensions from the inverse dynamics computation in blue dotted lines.

VI. Discussions

We can observe the following points in the experimental results:

1) The neuromuscular network model can accurately reproduce the muscle tension patterns in the walking motion. In addition, despite the lack of reference trajectory and difference in the contact conditions, the motion simulated with muscle tensions from the network model is reasonably close to the original motion.
2) Figure 4 shows that the neuromuscular network can generate trip behaviors qualitatively similar to elevating and lowering strategies. The ankle plantar flexion and the knee flexion make the obstacle avoidance behavior of the swing leg in CASE 1. Also the immediate contact of the swing leg with the ground is observed in CASE 2.
3) Figure 5 shows that the simulated muscle activities match the elevating and lowering behaviors. Pijnappels et al. [29] reported the EMG data of the supporting leg in normal locomotion and the elevating behavior after trips. Compared to their result, the large activations of Gastrocnemius and Soleus and the slight activation of Gluteus Maximus are similar, while the large activation of Hamstrings is not observed in our simulation.

This result has three implications:

- In robotics, it implies that a controller designed for a normal behavior (e.g., locomotion) may be able to immediately respond to disturbances before relatively slow controller switching or motion replanning can take place. Such combination of controllers will improve the robustness of balance control.
- In biomechanics, it confirms that it is indeed possible to produce the physiological observation that initial trip response occurs before any voluntary control can happen. However, the response of the voluntary control still remains an open issue.
- We have also been interested in experimental validation of our neuromuscular network model. The present result provides another validation with a more complex, coordinated behavior than the previous one [4], and therefore supports the validity of the global network structure and identification technique.

Several directions remain for future work. Our neuromuscular network model currently does not include contact information. We expect that adding sensory input on the contact state will significantly improve the simulated walking motion using the output of the neuromuscular network model. Another interesting direction is to compare the network model parameters with the models and controllers developed in the biomechanics field. For example, Hartmut et al. [30] developed a hand-tuned locomotion controller for a biomechanical biped model with a similar set of muscles as the one used in this paper. By comparing their feedback gains and our neural network parameters, we can verify if our data-driven approach can help the controller design for biped robots.

Our goal is to apply a similar approach to biped robot control, although it is not straightforward due to the different structure and actuators. A naive way to use the reflex model for a robot is to convert the sensor data and muscle

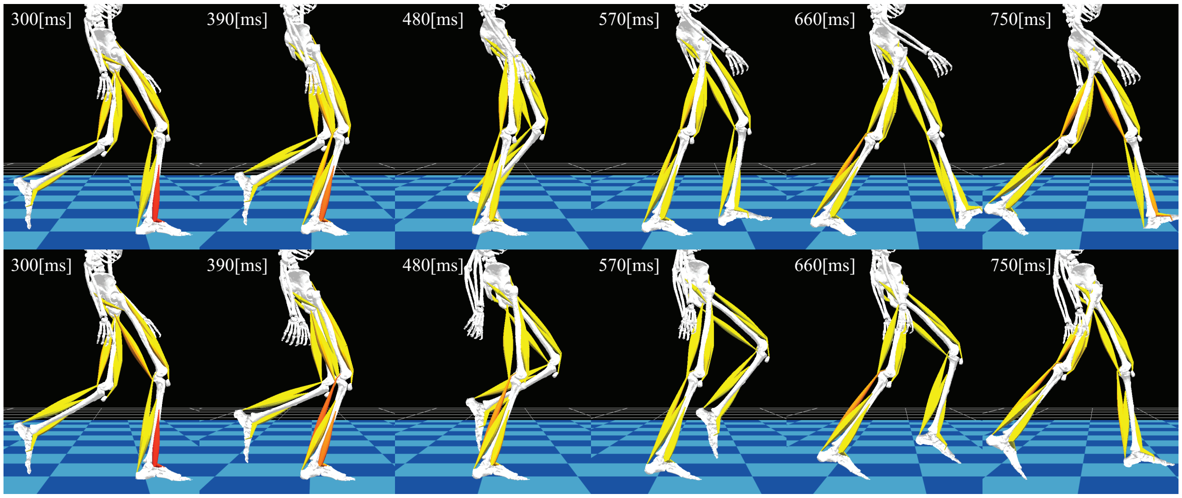

Fig. 3. Snapshots of the dynamics simulation of walking motion using the identified neuromuscular network model. Top row: normal walking motion used for the identification, bottom row: result of forward dynamics computation using the identified neuromuscular network model.

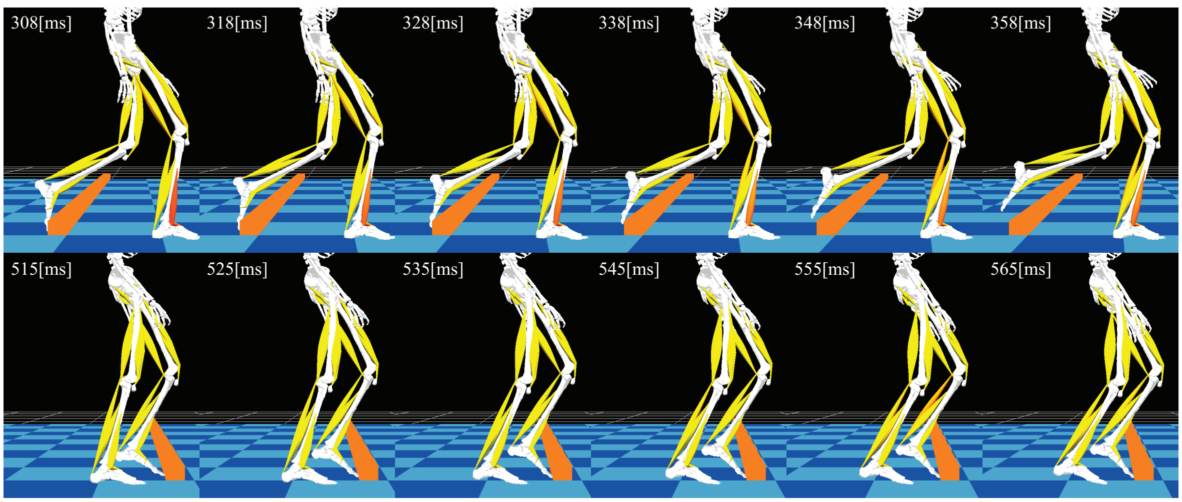

Fig. 4. Snapshots of the response behavior to the trip. Top row: CASE 1 (elevating), bottom row: CASE 2 (lowering). The obstacle hits the swing leg at 13 % of stride duration in CASE 1, and 55 % in CASE 2.

tension commands between a musculoskeletal model and the actual robot model. Sensor data such as joint angles can be converted to muscle length by forward kinematics computation of the musculoskeletal model. Similarly, the muscle tensions obtained by the reflex model can be converted to joint torques, which can then be commanded to the robot's actuators.

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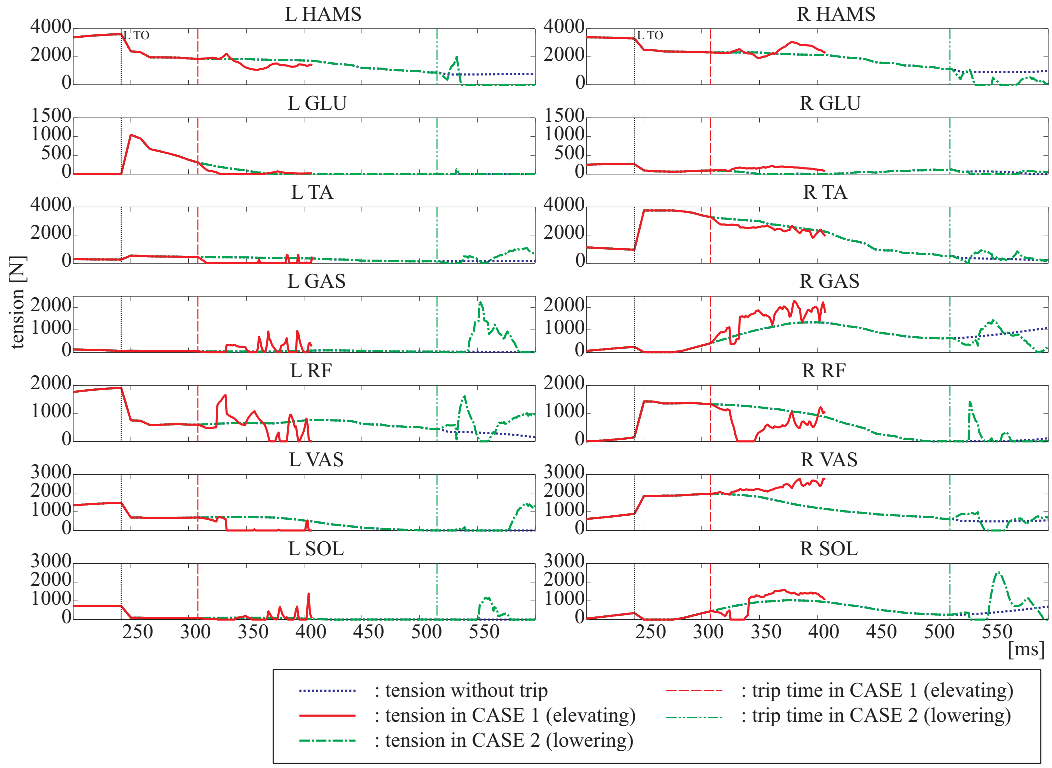

Fig. 5. The muscle tension during walking motion and the response to the trip. Blue dotted line: the muscle tension during walking motion without trip, red solid line: the muscle tension during walking motion with trip at 308 ms (CASE 1), green dashed-dotted line: the muscle tension during walking motion with trip at 515 ms (CASE 2). Black vertical dashed line: L TO (left toe off). During the time range shown in these graphs, the left heel is in the air and the right foot is in contact with the ground.

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