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Control Strategy for Assisting Paraplegic Patients

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Abstract-This paper studies the use of functional neuromuscular stimulation for stabilizing the standing posture of a human body. A skeletal-musculotendon-muscle activation dynamics model is used for the purpose of control strategy evaluation. The controller produces muscle activation, based on the proportional plus derivative control concept, to stabilize the skeletal dynamics with musculotendon torque. The performance and robustness of this controller are investigated. It can stabilize the standing posture even in the presence of variations in body segment mass and sensor noises. Due to limitation in the musculotendon forces and the number of musculotendon groups utilized, stability can be maintained only for initial positions that are reasonably close to the vertical configuration.

Keywords-*Spinal Cord Injury, Functional Neuromuscular Stimulation, Control*

I. INTRODUCTION

In the US, there are approximately 10,000 new cases of spinal cord injury (SCI) each year mostly caused by auto crashes, violence, falls and other accidents. The number of people in the US who are alive and have SCI has been estimated to be between 183,000 and 230,000. According to the National Spinal Cord Injury Database, depending on the age at injury and severity, the average lifetime health care and living costs that are directly attributable to SCI can vary from $339,000 to $2.1 millions per patient. These figures do not include any indirect costs such as loss in wages and productivity. Any improvement in the mobility functions of these SCI patients will have major financial and humanitarian impacts on our society. Functional neuromuscular stimulation (FNS)/functional electrical stimulation (FES) has been frequently studied as a way to improve the life of people with SCI by restoring the functionality of one's limbs through using electrical signals to stimulate the motoneuron.

A critical part of any FNS/FES system is its control unit. Many open [1-5] and closed [6-11] loop control ideas for FNS/FES have been proposed in the literature. In order to manage the complexity of mathematical analysis, many of these existing studies on FNS/FES control are based on simplified mathematical models of human body dynamics. For example, no muscle activation dynamics is included and a double inverted pendulum model is adopted in [9]. Use of such simplified mathematical models often impose unnecessary constraints, such as the use of ankle-foot orthoses in [9] to eliminate ankle rotation, that will reduce the effectiveness of these FNS/FES control concepts by making the patient's motion unnatural and demanding higher joint torques.

This paper presents extended research results based on the innovative FNS/FES control strategy proposed in [12]. It is based on a full-scale, detailed models of human body dynamics [13]. Using the minimum number of musculotendon groups, a paraplegic patient's standing posture can be stabilized, in computer simulations, even in the presence of variations in musculotendon parameters [12]. To evaluate the practical use of this FNS/FES control concept, its performance in the presence of other common uncertainties such as sensor noise and variations in body segments mass must be investigated. The human body dynamics model and control strategy used in this study are presented first followed by computer simulation results that show this FNS/FES control concept can provide robust performance in real world situations.

II. HUMAN DYNAMICS MODEL

A model of human dynamics that includes the interaction among the skeletal dynamics, joint torques, muscle forces, muscle contraction dynamics, muscle activation dynamics and input stimuli is summarized in the block diagram shown in Fig.1.

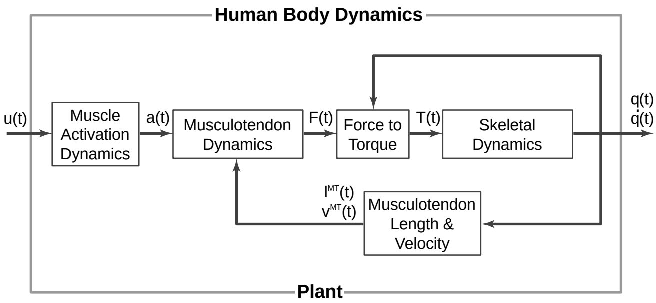

Figure 1. Block diagram of human body dynamics.

The skeletal dynamics model, shown in Fig. 2, is used to simulate how a body segment moves under a given torque and how it affects other segments. It is based on the assumptions of planar model, rigid body segments, bilateral symmetry and no excessive motion of the upper body segments [13, 14]. The anthropometric data used in the simulation is taken from [15]. A joint constraint model [16], which uses passive joint moment to prevent the joints from hyperextension, is also embedded in this skeletal dynamics model. The normalized musculotendon model discussed in [17] is used to compute all the musculotendon forces. The muscle activation model adopted in [8, 13] is also included in Fig. 1.

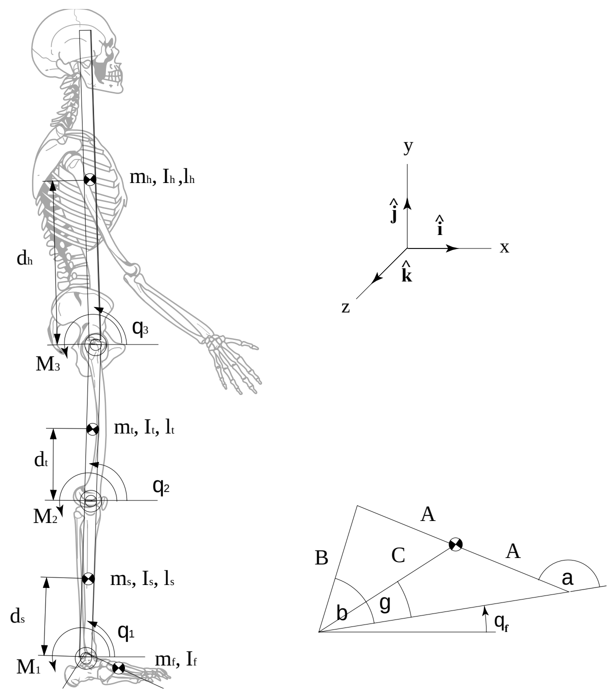

Figure 2. Planar model for standing posture and the foot model.

III. CONTROLLER DESIGN

To avoid introducing control redundancy, only three pairs, i.e. six, of flexor-extensor musculotendon groups are used in this control study, one pair for each joint in Fig. 2, to produce restoring torque in both directions. The states of the human body dynamics depicted in Fig. 1 can be partitioned into 4 groups:

$$x=\begin{bmatrix}\theta & \dot{\theta} & \overline{F} & a\end{bmatrix}^T \tag{1}$$

where:

θ is a 3x1 angular position vector,

$\dot{\theta}$ is a 3x1 angular velocity vector,

$\overline{F}$ is a 6x1 normalized force vector and

a is a 6x1 activation vector.

and the mathematical model of the human body dynamics is:

$$\dot{x}=f(x,u) \tag{2}$$

The controller design is restricted in several ways:

1. Bounded states. Some of the states are bounded or one-sided. For example, the musculotendon force cannot be negative.

2. Bounded input. Activation is bounded between 0 and 1 since the musculotendon cannot develop negative force and the activation is normalized ($a(t)$=1 is fully activated). The motoneuron input cannot exceed 1 without letting the activation surpass its upper limit. Thus, the motoneuron input $u(t)$ must be restricted between 0 and 1 as well.

3. Output feedback. The outputs or the measured states are the angular positions and the angular velocities of the body segments. Full state feedback cannot be used in this instance since the musculotendon forces and the activation states are unknown. Therefore, the controller's input must contain only the output states.

The block diagram of the closed-loop feedback system is shown in Fig. 3.

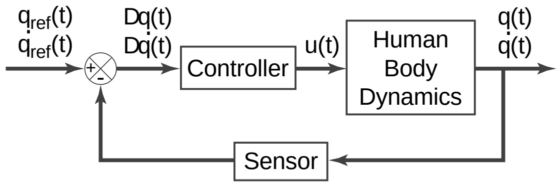

Figure 3. Closed-loop block diagram

Although there are many published literature on the control of nonlinear systems, most of them are unsuitable for stabilizing human body dynamics (2) around the upright standing posture. For example, the classical control design via linearization approach will not work well with a musculotendon model, such as the one adopted here, where many functions are one sided and not continuously differential. The high number of state and input variables makes offline training of a neurocontroller [18] too time consuming and therefore unrealistic. Online training of a neurocontroller [19] is also infeasible due to the unstable nature of human standing posture. The robust control approach proposed in [20] guarantees global stability for one-sided control system such as human body dynamics. However, its implementation requires full state feedback which is not available in this study.

Previous researches on the stabilization of systems [21, 22] similar to our human body dynamics show that the skeletal system presented in Fig. 2 can be stabilized by applying torques at its three joints using controllers based on the proportional plus derivative (PD) control concept, see Fig. 4. The design of such a controller for the skeletal dynamics can be based on its linearized model. If we can produce the output of the PD controller using the musculotendon, the skeletal dynamics can be stabilized. Based on the assumption that response time of muscle activation and musculotendon forces are substantially shorter than that of the skeletal dynamics, the controller design presented in Fig. 5 will be used in this study.

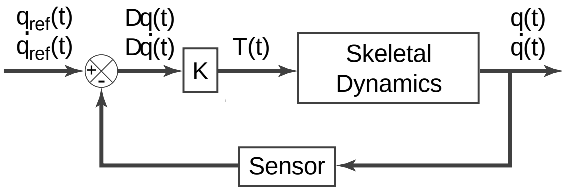

Figure 4. PD controller for the skeletal dynamics.

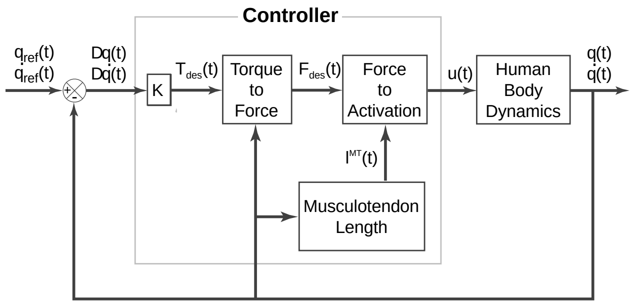

Figure 5. Block diagram of the proposed controller and human body dynamics.

As an example, a PD controller is designed using a state-space representation of the linearized skeletal model. At this point, the torques generated at the joints are generated by idealized servomotors and not limited by any shortcoming in the musculotendon groups. First, the PD gains are obtained using a pole placement technique. Then, these gains are used to stabilize the non-linear skeletal model. Since a person can react quickly and more stably when the knees are slightly bent and the body leans slightly forward, the command (reference) positions used in the simulation are slightly changed from the perfect upright configuration ($\pi/2$ rad for all body segments). Using these reference positions (shown as dashed straight lines in all body segment position response figures), the non-linear skeletal model with the PD controller is simulated and the result can be seen in Fig. 6.

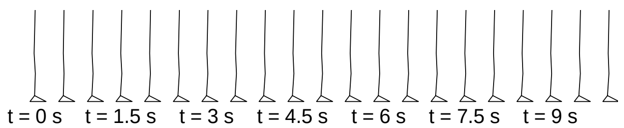

Figure 6. Time lapse plot of the skeletal model controlled with a PD controller.

However, a realistic musculotendon model differs greatly from the servomotors. There are differences between the desired torques and the actual musculotendon torques due to

1. Lag time: By estimating the input at a steady state condition, the controller introduces a lag time between the desired torques and the musculotendon torques.

2. Input constraints: The original constraint on muscle activation is still in place and it limits the musculotendon force. Furthermore, even on healthy and oft-exercised muscle, FNS can only generate a fraction of the optimal force. The efficiency of the electrical stimuli to contract the muscle is considerably less compared to the efficiency of the motoneuron and this is reflected in our simulations by reducing the upper limit of the input to the activation dynamics. From this point on, the inputs in all simulations saturate at 0.7 (i.e. $0 \leq u(t) \leq 0.7$). In other words, only 70% of the optimal muscle force can be generated isometrically by the musculotendon.

Fig. 7 shows that, due to the difference between the desired torques and the musculotendon torques, the posture oscillates slightly. Also, small steady state errors persist in the position response of the body segments. These steady state errors can be corrected by adding integral action to the PD controller. However, the control action prediction controller can still maintain balance and stabilize the standing posture.

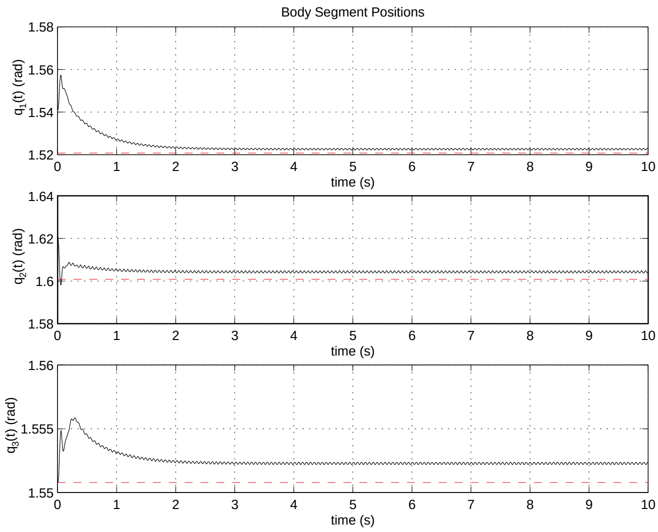

Figure 7. Positions of the body segments of the skeletal model.

IV. BODY SEGMENT MASSES

The controller robustness is investigated by changing the parameters of the human body dynamics, notably the mass of body segments. To avoid doing too many computer simulation runs, all parameter variations are carried out uniformly on every element in the system. For example, when the segment mass is underestimated by 10%, it applies to all 3 segments of the skeletal model. Fig. 8 shows that the controller can still stabilize the standing posture even when the mass is underestimated by 50% of the nominal values listed in [15]. However, the figure shows that the system starts to behave rather erratically, that is, the steady-state positions deviate farther away from the reference positions and the amplitude of the oscillation grows as well. Just as underestimating the mass values, overestimating the mass values also degrades the performance of the controller, as can be seen in Fig. 9, even when the controller stabilizes the standing posture. At 2.5 times the original masses, performance of the controller degrades substantially. The feet start to tip either about the toes or about the heels. At this point, the controller is considered incapable of maintaining the standing posture.

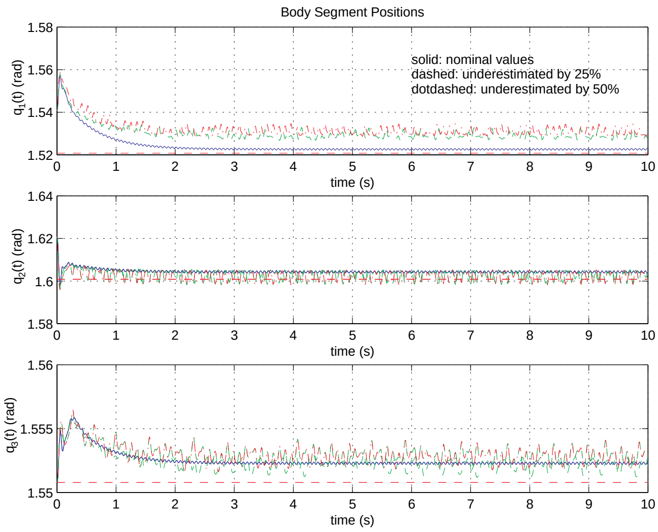

Figure 8. The effect of underestimating the mass of body segments on the standing posture.

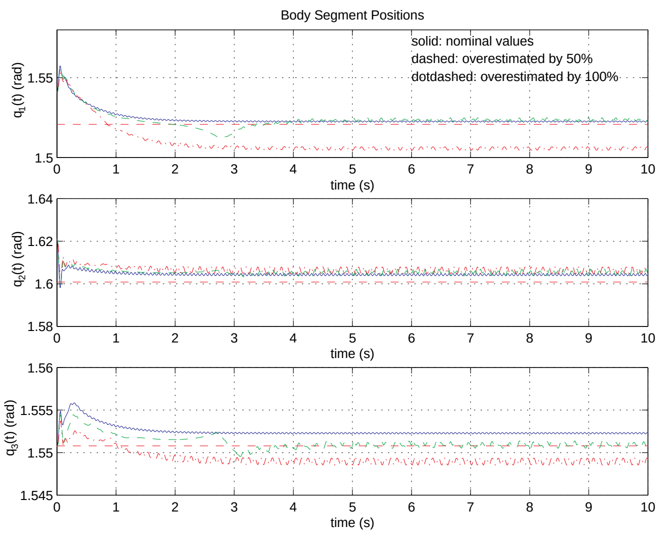

Figure 9. The effect of overestimating the mass of body segments on the standing posture.

V. SENSOR NOISES

Some white noise is added to the output of the angular positions of the body segments to simulate sensor noise. Noise power is set at 10^{-8}, and covariance of the noise is 10^{-5}. This translates to random noise with maximum amplitude of about 0.025 rad. The standing posture is stable albeit some increased oscillations. The skeletal model is then simulated with noise power increased to $5x10^{-8}$. The standing posture is still stable with much more visible oscillations, Fig. 10. As the noise power equals to 10^{-7}, the plant is no longer stable.

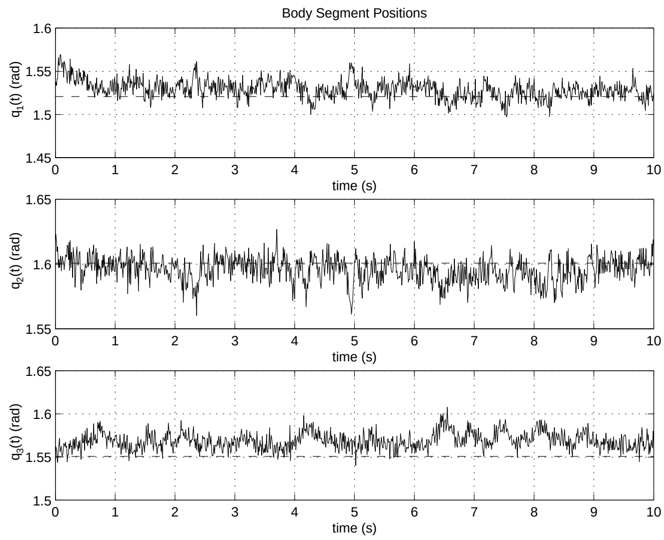

Figure 10. Standing posture with sensor noise in position.

Another noise block is then used to simulate sensor noise in body segments' angular velocity. As shown in Fig. 11, the controller stabilizes the standing posture in the presence of those noises.

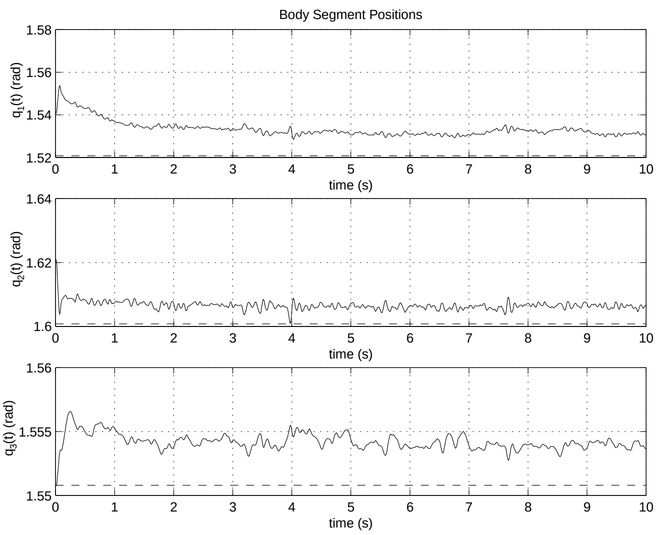

Figure 11. Standing posture with sensor noise in velocity.

Similarly, white noise is also added to both positions and velocities of the body segments since most likely noise will occur in both positions and velocities in real life. Performance of the controller starts to degrade in this case although independently the noises do not affect the posture very much. Also, the body segment positions (Fig. 12) show trend similar to that found in the position sensor noise. From the time lapse plot (Fig. 13), it can be seen that the posture is not good. However, the skeletal model remains stable and does not tip about the heel nor the toe.

strong enough to make a skeletal model rise to an upright position from a sitting position, especially when the activation level is further decreased to 70%. However, this may not be a major concern since voluntary trunk motion and arm support usually contribute to the process of standing up from a sitting position [23].

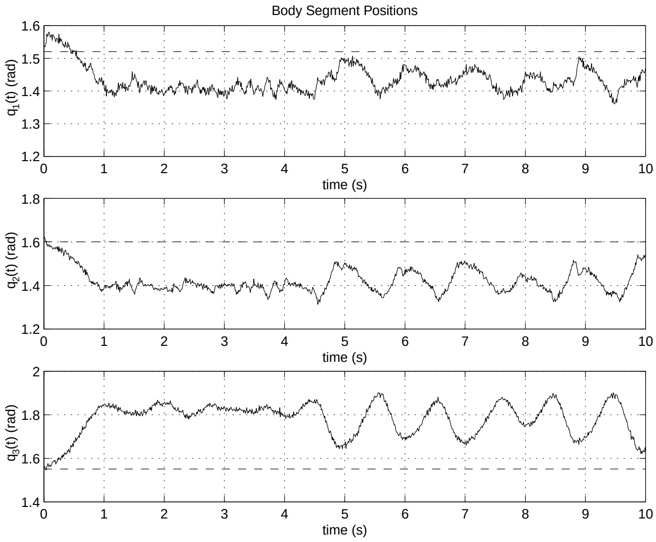

Figure 12. Standing posture with sensor noise in both velocity and position.

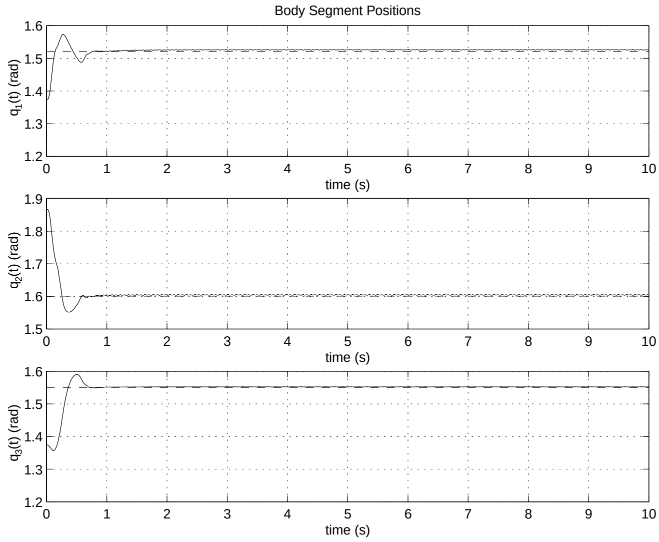

Figure 14. The body segment positions as they recover from initial positions.

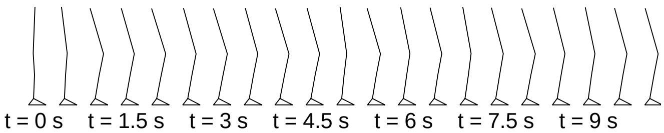

Figure 13. Time lapse of standing posture with sensor noise in both velocity and position.

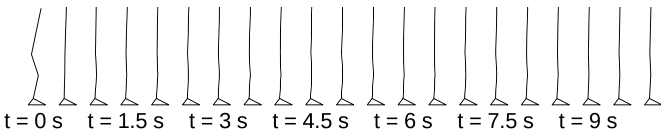

Figure 15. Time lapse plot of the recovery from initial positions.

VI. INITIAL CONDITIONS

So far, all the simulations are done with an initial condition that is rather close to the reference positions. However, the effect of starting the simulation from different initial positions still needs to be studied. Computer simulations show that the stability of the skeletal system depends greatly on the initial conditions. Figs. 14 and 15 show the recovery of the standing posture from an initial condition which is farther away from the reference positions. The skeletal system cannot recover from initial positions that are too far away from the reference positions. In fact, it cannot recover from twice the initial deviations shown in Fig. 14. This problem arises not from the PD controller, but from the magnitude of available musculotendon forces. The PD controller can make the skeletal model go from a sitting position to the upright position using idealized servomotors as actuators. However, the same thing cannot be said for the one using musculotendon actuators, which would fall almost right away. Comparing the desired torques and the actual musculotendon torques shows large discrepancies. That is because 6 musculotendon groups are not

VII. CONCLUSION

A control strategy for FNS/FES system is outlined in this paper. It is a combination of a PD controller for the skeletal model and the control action prediction concept for musculotendon activation. It is demonstrated in computer simulations that this approach can stabilize the standing posture with the minimum number of musculotendon groups. The controller can withstand reasonable levels of sensor noises and variations in the segment masses. The controller can correct the initial posture to the desired standing posture as long as the initial posture does not deviate too far from the desired standing posture. Minimal number of musculotendon groups and lower activation level prevent the controller from generating large joint torques necessary for correcting large initial deviations from the desired posture.

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