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Frequency Sensitive Motion Control for a Single Joint Arm Model

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Abstract—**The proposed feedforward controller is composed of three parts: a lookup table controller, an artificial neural network controller and a decision block. The lookup table controller has the information about the relation between the activation levels of muscles and the output at steady state. To compensate for the delayed tracking ability of the lookup table controller for rapid movement, an artificial neural network (ANN) controller is used in parallel with the lookup table control. The ANN controller is trained to learn the inverse dynamics of the musculoskeletal model. The decision block determines the contribution ratio of each controller based on the frequency analysis of the reference trajectory. The control algorithm was tested on single joint elbow model with a flexor and an extensor. Results show that the combined controller reduces the overall output errors.**

I. Introduction

Functional Electrical Stimulation (FES) is used to restore voluntary movement of patients who have lost motor control because of injuries or neuromuscular diseases. Because of the difficulty of controlling highly nonlinear, time-varying and highly coupled musculoskeletal systems, many different control algorithms have been tried for functional neuromuscular stimulation [1].

One of the methods to build a controller for FES is to mimic the way the brain controls human voluntary motion. There are two hypotheses trying to answer how the human brain controls voluntary movement. One is equilibrium point hypothesis (EPH) and the other is inverse dynamics model (IDM). In the inverse dynamics model, the brain is believed to have the inverse dynamics of a musculoskeletal system [2]. In this hypothesis, the brain sends appropriate activation signals for each muscle to obtain the desired joint angle movement, even in cases with external loads. However, because of the complexity and redundancy of the musculoskeletal systems, it is challenging for FES controller to find inverse dynamics of the systems as the degree of freedom to control increases.

In the equilibrium point hypothesis, the brain does not have all the information about inverse dynamics. Instead, it uses spring-like intrinsic properties of muscles to set the trajectory of equilibrium points [3].

The Hill-type muscle model [4] is one of the most widely used muscle models for computer simulation. In isometric contraction, the damping element of muscles generates little force, and the muscle behaves like a spring. Therefore, by changing the spring constant, which is the stiffness of the muscle, it is possible to shift from one steady state output angle to another steady state output angle [5]. However, it does not predict the transient response precisely.

Feedback control reduces sensitivity to internal parameter variation and external disturbance. However, the output sensors necessary for feedback are not always available in FES. In addition, good feedforward controller can improve the overall performance when it is combined with feedback controller [6].

In this paper, we propose a new feedforward control algorithm that combines the benefits of both spring-like properties of muscle and IDM In the proposed control algorithm, we separated a steady state control method based on the spring-like properties of the muscle and inverse dynamics model based on the black box input-output system.

II. Methodology

A single joint human elbow model with biceps and triceps is used for this simulation. For the biceps and triceps muscle models, the Hill type muscle model is used [4][7]. The input to each muscle is the activation levels between 0 and 1, where 0 means no activation and 1 means maximum activation. The maximum forces for biceps and triceps are 250N and 600N respectively. The optimal muscle fiber length for biceps and triceps are 13.6cm and 10.2cm respectively and first order activation dynamics with a time constant of 30ms is used. The output of the system is joint angle where 0 degrees means full extension. The arm is placed on a horizontal plane and gravity is ignored during the motion.

The overall block diagram of the proposed controller is shown in figure 1. The proposed controller is composed of three parts: a look up table controller, an artificial neural networks (ANN) controller, and a decision block.

The lookup table controller contains the relations between the desired output angles and the activation levels of the muscles (figure 2). These relations are obtained by stimulating biceps and triceps at constant levels and measuring the output angles (figure 3). Because of intrinsic spring-like properties of muscles, the output angle converges to a constant value after some transient time when the activation levels of both agonist and antagonist muscles are maintained at constant levels. Therefore, the output angle can be changed from one to another by co-activation of biceps and triceps [5]. However, for the same desired output, there are numerous combinations of muscle activations (figure 2). To remove the redundancy in

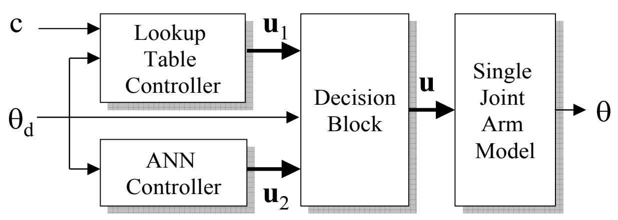


Fig. 1. Block diagram of the proposed controller. $\boldsymbol{\theta_d}$ is the desired output and $\boldsymbol{\theta}$ is the system output. **u** is the total controller output and fed into the joint model as the activation level for biceps and triceps. $\mathbf{u_1}$ is the lookup table controller output and $\mathbf{u_2}$ is ANN controller output. c is the co-activation level.

activation levels for a specific output angle, the co-activation level, which is defined as the sum of agonist and antagonist muscle activation, is fed to the lookup table controller as additional information. The higher the co-activation level, the stiffer the arm becomes.

Because the input-output relations in the lookup table controller are based on constant activation levels of muscles, the transient response can be slow for rapid movement. To compensate for the slow response, an ANN controller is added in parallel with the lookup table controller. The ANN controller is trained to learn the inverse dynamics of the musculoskeletal system. Low-pass filtered random signals for biceps and triceps activation are fed to the system model and the output angle trajectory is stored for training purposes. The input to the ANN controller is the time series of the stored output angle and the outputs of the ANN are the activation levels used to obtain the output trajectory. Because there is a time delay in muscle activation, the sampled output angles at the time duration from 20ms to 60ms after the activation input are used as inputs to the ANN and the sampling period is 10ms. For the ANN, a multilayered feedforward neural network with error backpropagation for training is used.

A decision block is added to determine how much of each controller will contribute to the total output. The total control output *u(t)* can be expressed as follows:

$$u(t) = (1 - w(\theta_d))\, u_1(t,c) + w(\theta_d) * u_2(t) \qquad (1)$$

,where u_1 is the lookup table controller output and u_2 is the ANN controller output. The co-activation level *c* removes the redundancy in the lookup table controller. The weight *w* is the contribution ratio of the ANN controller between 0 and 1 and *w* is determined by frequency components of the desired output at the decision block. For fast movement, large *w* is required, and for steady state, *w* is set to zero. In the decision block, short time Fourier transform(STFT) is computed for 1 second Hanning windows to find the frequency components of the desired trajectory. Because there is no feedback, the weight *w* can be calculated in prior to the actual control signal generation. Before STFT is done, the mean value is subtracted to remove DC component. By the removal of DC component, STFT becomes zero in all frequencies for a constant desired output. Then the amplitude at each frequency is multiplied by properly tuned parameters.

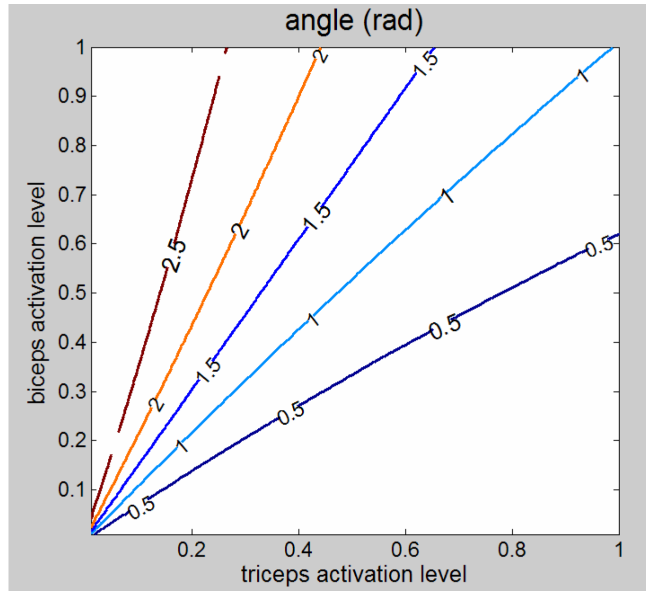


Fig. 2. Input output relation in lookup table. The numbers on each line indicate the joint angles in radians. For a desired output angle and co-activation level, the biceps and triceps activation levels are uniquely selected.

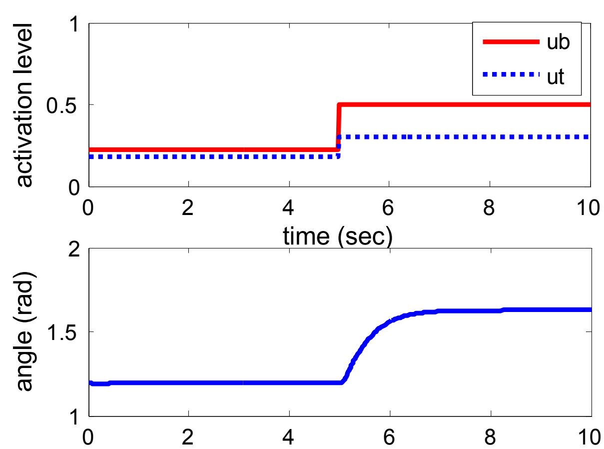


Fig. 3. A sample output angle for activation levels. The output angle converges to a certain value when the activation level changes from one value to another. ub is biceps activation and ut is triceps activation.

III. Results

Figure 4 shows the simulation results of the three different controllers. Figure 4(a) is the result obtained when only the lookup table controller is used. The dotted line is the desired trajectory and the solid line is the actual system output. The system output is very close to the desired output at steady state. However, the lookup table controller is slow to track the reference trajectory for rapid movement. The reason of the lag is that the lookup table is built on a steady state input output relation. The delay in response for fast movement does not decrease much by increasing the co-activation level (figure 4(b)). Figure 4(c) shows the results when only the ANN controller is used. The results show reduced tracking error during the rapid movement. However, the steady state error is larger than those of figure 4(a) and 4(b). This indicates that the state output angle (0.7 rad in this simulation) may be not included in the training data set, and the ANN does not generalize the input output relation as accurately as the lookup table controller. The combined controller shows good trajectory tracking results for both rapidly changing and steady state desired trajectory (figure 4(d)).

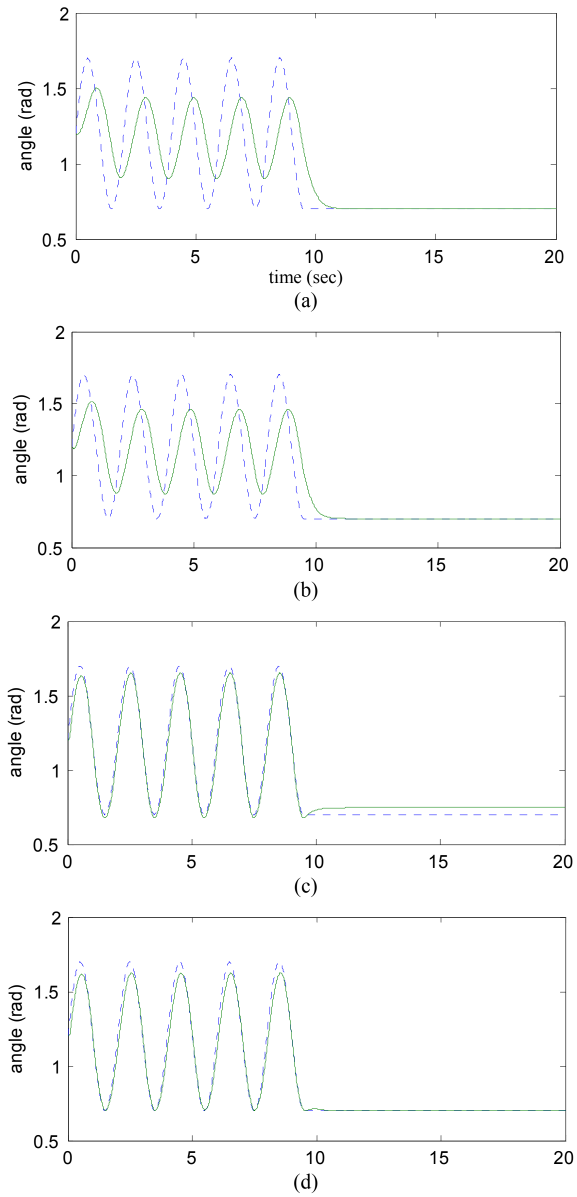


Fig. 4. The dotted line is the desired input and the solid lines are the actual elbow angle. (a) joint angle when only lookup table controller is used (c=0.5) (b) joint angle when only lookup table controller is used with higher co-activation (c=1.0) (c) joint angle when only ANN controller is used (d) joint angle when the proposed controller is used.

Table I shows the output errors of the three controllers. For the ANN controller, 10 different neural networks are used. Each ANN has one hidden layer and the number of nodes in the hidden layer varies from 20 to 50. For the hidden layer transfer function, hyperbolic tangent sigmoid function is used and for the output layer transfer function, log-sigmoid function is used. Low-pass filtered random signals with either Gaussian distribution or uniform distribution are used as training trajectories for activation levels. For the steady state error calculation, constant desired outputs from 0 degrees to 160 degrees with one degree resolution are used. The results show that the combined controller maintains the advantages of the lookup table controller and the ANN controller, which are small steady state errors and fast tracking performance respectively.

	Steady state errors	Random Trajectory errors
Lookup table	0.02 (0.06)	9.96 (6.93)
ANN	3.10 (3.14)	2.32 (1.85)
Combined	0.02 (0.06)	2.51 (2.04)

Table I. The comparison of each controller output errors. The co-activation level for lookup table controller is set to 0.5. The units are degrees. The numbers in parentheses are standard deviations. The error is defined as the mean value of the absolute difference between the desired output and the measured output.

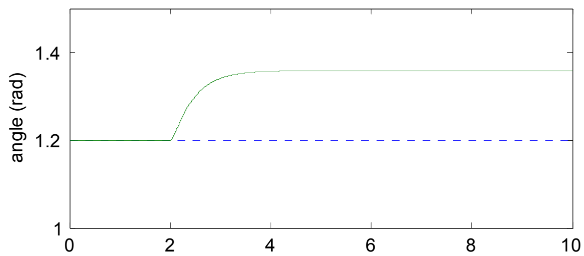
IV. Discussion

The proposed control algorithm combines an ANN control using the inverse model and a lookup table control using the intrinsic spring-like properties of muscles. In this model, the training of the inverse model is critical for the performance during the rapid movement. Therefore, the proper choice of neural network parameters and training trajectory is important for the general output performance.

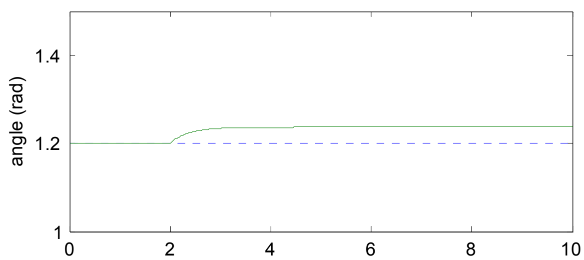
The velocity profile of the reaching motion is bell shaped and the final position error is more important than transient trajectory error in the reaching motion. For this kind of motion, the proposed control reduces the steady state error and is independent of the training result of the ANN.

One of the disadvantages of open loop control is that it does not respond properly to external disturbances because it cannot detect them. However, higher co-activation levels reduce the effect of external disturbances at the cost of higher energy consumption for muscle activation (figure 5). In the case of ANN control using inverse dynamics, the co-activation levels cannot be arbitrarily chosen.

Because the proposed controller is a feedforward controller, the frequency component of the desired trajectory can be pre-computed before the start of the movement. For this reason, a more complicated decision algorithm can be incorporated. The proposed control can be extended to multi-degree of freedom cases by proper choice of inputs and outputs.



(a)



(b)

Fig. 5. Look up table controller output with external disturbance 1 Nm at 2 second. (a) is for c = 0.5 and (b) is for c=1.0 (Dotted line is the desired trajectory and solid line is the system output trajectory)

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REFERENCES

[1] P. Crago et al. “New Control Strategies for Neuroprosthetic systems” *J Rehabil Res Dev,* 33(2), 1996

[2] MA Conditt et al. (1997), “The Motor System Does Not Learn the Dynamics of the Arm by Rote Memorization of Past Experience”, *Journal of Neurophysiology*, 78:554-560, 1997

[3] E Bizzi et al. “Does the nervous system use equilibrium-point control to guide single and multiple joint movements?”, *Behavioral and Brain Sciences*, 15: 603-613, 1992

[4] F. Zajac “Muscle and tendon: properties, models, scaling, and application to biomechanics and motor control” *JCrit Rev Biomed Eng. Rehabil Res Dev,* 17(4): 359-411, 1989

[5] N. Hogan, “Adaptive Control of Mechanical Impedance by Coactivation of Antagonist Muscles.”, *IEEE Trans. Automatic Control,* 29(8): 681-690, 1984

[6] Kurosawa et al. “Joint Angle Control by FES Using a Feedbaack Error Learning Controller”, *IEEE Trans Neural Syst Rehabil Eng.* 13(3):359-71, 2005

[7] M. Lemay and P. Crago, “A dynamic model for simulating movements of the elbow, forearm, and wrist” *Journal of Biomechanics*, 29(10): 1319-1330, 1996