SIMULATION OF THE STS TRANSFER USING A MLP WITHOUT EMBEDDED INTERNAL FEEDBACK

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Abstract

In FES-controllers developed based on a tracking approach, the desired movement in a specified space (e.g., trajectories of the joint angles) is used as the input of the controller. In answer to the question how the desired movement for each particular subject should be defined, a new method has been developed to generate the subject-dependent trajectories of the joint angles during the sit-to-stand (STS) movement.

Introduction

Many researchers have been worked on the prediction of the STS (e.g., [1]-[3]). In most of these works, the movement is predicted by applying different optimization algorithms with different object functions. Moreover, body-skeletal dynamics is described by applying movement equation for different links (depending on the degree of freedom used in the model). One of the important questions in these methods is to find a suitable trade-off between the exactness of the mathematical model and the complexity of the calculations. The un-modeled dynamics is another question to be answered in the model-based methods. Considering all of these questions, in this work an algorithm is proposed that is based on the nonlinear characteristics of the artificial neural networks (ANN). A Multi Layer Perceptron (MLP) with one hidden layer including 42 neurons was implemented. Using this method, reconstructed joint angle trajectories had errors of less than 4%. Moreover, in comparison with a model-based algorithm which uses a mathematical description of the body-skeletal dynamics, this method predicts the flexion of the upper body before leaving the seat more accurately.

Material and Methods

Model

To define the movement pattern, the body skeletal system was simplified to a rigid three-link model in the sagittal plane. The links represent the shanks, thighs and upper body. Thereby, ankle, knee and hip joint angles plus the length of each link describe uniquely the body-state at each moment in the sagittal plane.

The Neural Network

An MLP with one hidden layer including 42 neurons was implemented. Activation function of the hidden layer was sigmoid and activation function of output layer was linear. The input data for the MLP network are the limb lengths and the body height and weight, and given initial and final body states (initial sitting position and the final standing posture). These values are derived from recorded STS tasks performed by 6 subjects.

Outputs of the implemented MLP are the coefficients of the Fourier Half Amplitude Cosine Expansions (FHACE) of the joint angles. Trajectories of the joint angles are reconstructed with the help of these coefficients (see Fig. 1). During the learning process, the calculated error between the desired joint angles (obtained from recorded movements) and the reconstructed ones are fed back to the MLP (global feedback). In usual approaches, an internal feedback in the body of the MLP implements the dynamics of the modeled systems. Since the coefficients of the FHACE describe the inherent dynamics of the body-skeletal system, we could avoid the feedback in the body of the MLP. Back propagation (BP) method was used to get the optimized weights for the MLP.

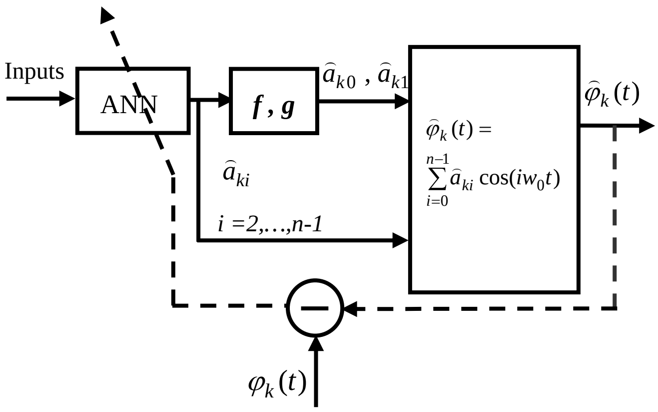

Fig. 1: Implemented MLP system with the global feedback used in the process of learning. Where, $\varphi_k(t)$ is the *k*th joint angle at time *t* and $\hat{\varphi}_k(t)$ is the estimated *k*th joint angle; and *k=1* for the ankle joint, *k=2* for the knee, and *k=3* for the hip; a_{ki} is the *i*th coefficient of FHACE of the measured *k*th joint angle and $\hat{a}_{ki}$ is the *i*th estimated coefficients.

Learning Data

The STS movement of six healthy subjects has been recorded. Each subject repeated the task 20 times. 16 out of 20 movements of each subject have been used for the learning process of the MLP. Input data was normalized between 0 and 1.

Results

After completing the learning process, the recorded movements, which have not been used during learning procedure, were applied as recall ones. Using this method, maximum error of the reconstructed trajectories was less than 4% (Table 1).

The implemented system has been used to predict the movement of a subject whose data were not used in the process of the learning. The resulted movement had a satisfactory similarity to the measured one. The maximum errors are depicted in Table 2.

Table 1: Percentage of the maximum error of the predicted trajectories. The values of the maximum errors are averaged over six subjects.

Maximum Error	**Training**			**Recall**		
	Ankle	*Knee*	*Hip*	*Ankle*	*Knee*	*Hip*
	4.0	3.7	1.8	3.9	3.6	2

Table 2: Percentage of the maximum error of the predicted joint angle trajectories for a new subject.

Maximum Error	**New Subject**		
	Ankle	*Knee*	*Hip*
	5.6	10.2	5.1

Our results indicate that the prediction of the ankle and knee joint angles was accomplished with a higher rate of the error relative to the hip joint angle.

Stability of the predicted movement after leaving the seat (i.e., the position of the center of pressure, COP, under the two feet) was investigated. For all of the predicted movements COP was under the feet.

Discussion

One of the important features of this method is the application of the FHAC expansion. This helps us to be able to implement a global feedback during the learning process, which reduces the complexity of the system. It should be recalled that the internal feedback increases the dimension of weight matrix in a MLP network, which in turn means more complexity.

In comparison with a model-based algorithm, which used an explicit mathematical description of the body-skeletal dynamics (e.g., [1], [2], [5], and with a maximum error of the predicted hip angle of 10.5%), this method predicted the flexion of the upper body before leaving the seat more accurately.

References

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