EMG-BASED JOINT TORQUE ESTIMATION USING PHYSICS-INFORMED NEURAL NETWORK IN HUMAN UPPER LIMB

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Introduction

When employing an exoskeleton or exosuit to augment strength and endurance, one must be able to calculate the joint torque of hand movements using surface electromyography signals. The calculated joint torque is sent to the actuator of the external device as a control signal. The musculoskeletal model can be used to estimate joint torque [1]. However, this paradigm has a slowdown problem, particularly in real-time applications. Due to the advantages of quick and easy implementation, data-driven approaches have recently become an attractive option; however, they suffer from accuracy during task variations [2]. In this study, a physics-informed neural network for joint torque estimation is proposed; first, we have predicted the joint angle, which was further used to compute joint torque using a derived equation of motion. Here, physics-based domain information is included in the data-driven model via the channel of the customized loss function. To illustrate the joint torque prediction in the suggested framework, we employed the surface ElectroMyoGram (sEMG) and time. The validation used self-reported data from a single healthy person for several elbow flexion trials. The outcome shows that the suggested framework is reliable and effective.

Methods

An sEMG input layer, an output neural layer, and four hidden layers make up the Artificial Neural Network (ANN) model utilized to estimate elbow joint angle (where the relation between sEMG and joint angle was facilitated). This model is further improved by the physics-based component entailing the underlying relationship between joint angle and joint torque, as shown in Fig. 1. In order to apply a physics-based constraint, a customized loss function is used.

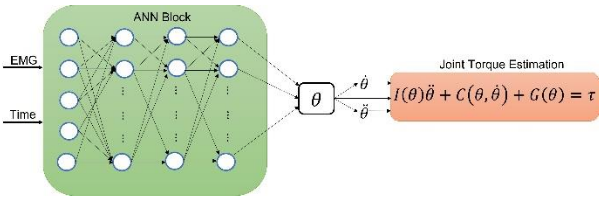

Figure 1. The framework of physics-informed neural network. Inputs to ANN are sEMG signals and time. The output of ANN is joint angles which are further used to estimate joint torque.

The customized loss function in the proposed framework is defined as follows:

Total loss = Joint angle loss + Joint torque loss

$$\text{Joint angle loss} = \frac{1}{N_u}\sum_{i=1}^{N_u}\left|\theta_p\left(emg_u^i, t_u^i\right) - \theta^i\right|^2$$

$$\text{Joint torque loss} = \frac{1}{N_f}\sum_{i=1}^{N_f}\left|\tau_p\left(\theta_p^f, \dot{\theta}_p^f, \ddot{\theta}_p^f\right) - \tau^f\right|^2$$

where θ_p and θ are the predicted and actual joint angles, respectively. τ_p and τ are the torque from predicted and actual joint angles, respectively.

Results

The predicted torque from the physics-informed neural network agreed with the torque from inverse dynamics calculations for the elbow flexion motion, as shown in Fig. 2.

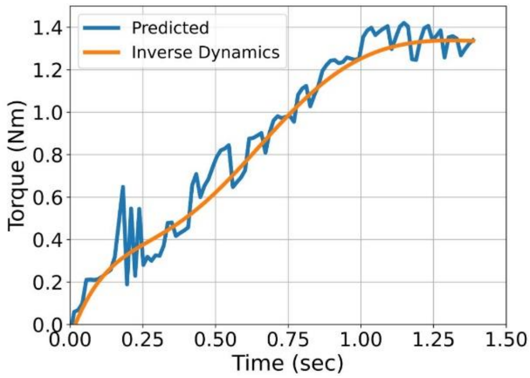

Figure 2: Comparison between predicted joint torque and inverse dynamics torque for elbow flexion motion.

Discussion

Our model predicts elbow joint torque with reasonable accuracy, compared to the joint torque from an inverse dynamics model. The variation in the prediction may be due to overfitting and noise in experimental data for the given activity, indicating the need for the optimal architecture of ANN.

References

1. Durandau et al, J. Neuroengineering and rehabilitation, 16:1-18, 2019.
2. Zhang et al, IEEE Trans. Autom. Sci. Eng, 18:564, 2020.