PHYSICS-INFORMED NEURAL NETWORKS FOR PREDICTING FATIGUE DURING INTERMITTENT ISOMETRIC TASKS

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Introduction

The state-of-the-art in musculoskeletal dynamics estimation is *Physics-Informed Neural Networks* (*PINNs*), which are standard machine/deep learning models that exploit physics law equations by integrating them into the loss function in order to penalize the estimation of forces and/or kinematics of a virtual character [1]. Unlike finite element and conventional physics-based methods, PINNs do not require to explicitly model the complex underlying physics that govern the human body, and as showed in [1][2], they can be physically consistent while being more fast compared with neural network architectures such as CNNs and LSTMs.

In this work, we developed a PINN for predicting knee torques during intermittent isometric fatiguing tasks inspired by the *Three-Compartment Controller Model* (*3CC*) [3][4], which is a state machine that describes the transition of all muscle motor units of a human limb from one state (compartment) to another, namely active (M_A), fatigued (M_F), or resting (M_R). Our model predicts the mean torque of the knee (in %MVC – maximum voluntary contractions) during active (M_A) and fatigue state (M_F) and can be used to both synthesize/simulate fatigue-driven motion for realistic 3D character animation as well as model temporally evolving ergonomic effects.

Methods

Our Physics-Informed Neural Network (Figure 1) consists of a three-layer Bidirectional Long Short-Term Memory (BiLSTM) network with 128 units, and a fully connected output layer. BiLSTM is an extension of LSTM that also has backward feedback connections along with forward ones, which aid the model to exploit both future and past data w.r.t. a specific time step, and as a result is more accurate than LSTM [5]. The model is fed with time steps (sec) and M_A and M_F (%MVC) of the current step (t) to produce knee mean torques of active and fatigue state of the next time frame ($t+1$). The loss of our model is defined as follows:

$$L = MSE + \frac{1}{T}\sum_{t=0}^{T}\left(\frac{\partial M_F}{\partial t} - F \cdot M_A + R \cdot M_F\right)^2 \quad (1)$$

$$\frac{\partial M_F}{\partial t} = F \cdot M_A - R \cdot M_F \quad (2)$$

where MSE is the mean square error of the prediction, F and R show at which rate the motor units fatigue or rest, respectively (for knee joint F = 0.01500 and R = 0.00149 [3]), and Eq.2 is the differential equation that describes fatigue state as presented in [3][4].

We implemented and trained our model using Python's Tensorflow. The training dataset was obtained from [6] and consists of mean torques of the knee joint from 8 healthy (aged 29 ± 6 years old) subjects during intermittent isometric maximal voluntary contractions of the quadriceps while seated.

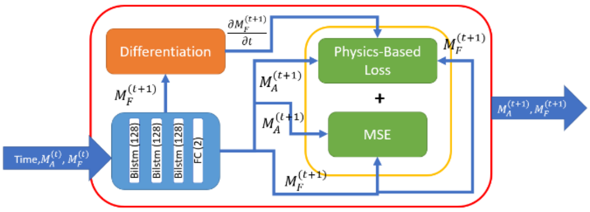

Figure 1: A general overview of our PINN.

Results

We compare the performance of our PINN with other architectures in terms of Normalized Root Mean Square Error (NRMSE) as shown in Table 1. Lower values indicate accuracy and good performance.

Method/NRMSE	M_A	M_F
PINN (Ours)	3.01	3.95
LSTM	3.91	4.66
ANN	5.87	6.12

Table 1: The NRMSE values for mean torques during active and fatigue state (ANN – Artificial Neural Network).

Discussion

The primary goal of this work is to provide an automatic and fast solution of predicting fatigue without using physics-based methods. According to the results, our approach performs better than standard architectures, thus, indicating that our PINN models effectively the fatigue state of 3CC. As future work we would like to model all three states of the 3CC into one deep learning network and utilize/test our model to predict the fatigue of an animated virtual character in real-time.

References

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