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On the Ability to Identify the Knee Joint Position Under Neuromuscular Electrical Stimulation Using Long Short-Term Memory Neural Networks

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Abstract. Neuromuscular Electrical Stimulation (NMES) has been applied in many treatments of spinal cord injured patients providing many social and health benefits. While commercial stimulators are designed in open-loop there are many studies on closed-loop NMES systems that require an adequate mapping over the delivered electric stimulus and achieved angular position (or torque). On the other hand, Recurrent Neural Networks (RNNs) offer a promising possibility for identifying and modeling dynamic nonlinear systems. One of the most popular and applicable RNN is the Long Short-Term Memory (LSTM) architecture. Hence, this paper investigates the effectiveness of the LSTM in the specific task of identifying the knee joint angular position under NMES using experimental data from three male healthy individuals. As shown in results, the LSTM model demonstrated to be an effective estimator for this application, proving to be a prospective method for deeper investigation on nonlinear system identification and modeling.

Keywords. Knee joint, electrical stimulation, Long Short-Term Memory, spinal cord injury, system identification.

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1 Introduction

Spinal Cord Injury (SCI) concerns to damages to the spinal cord, which can be caused by traumatic reasons (e.g., violent acts, falls, and road traffic crashes) or nontraumatic ones (e.g., tumors, disease or degeneration of the neurological tissue). SCI leads to problems such as partial or total paralysis; loss of sensation and function of muscles; muscle atrophies; a lot of pain to the individual; and it can negatively affect others human body systems.

An effective approach for treating SCI is the use of Neuromuscular Electrical Stimulation (NMES), which provides many health and social benefits for its patients, offering higher expectation and quality of life. NMES is a technique based on the application of a potential field across the motor neurons to generate a muscle contraction via surface or intramuscular electrodes. Several investigations for NMES systems on knee joint control have been reported in the literature consisting of two main lines, controlling and modeling. However, an efficient mapping describing the relationship between the muscular model and stimulation parameters is a very strict requirement for developing powerful feedback control techniques, motivating the main focus of this paper.

Moreover, nonlinear systems identification and modeling have been applied in most areas of science to predict the future behavior of dynamic systems. On the one hand, there are mathematical models, which are based on the description of systems using its physics and mechanics. Notwithstanding, there are black-box models, which are based on the direct input/output relationship based on data.

In the literature, one can find different models of electrically stimulated lower limbs mainly divided into the two main approaches, mathematical models [3, 7], and black-box ones [1, 6]. As muscles present several time-varying properties including nonlinearities; and motivated by a high power for computation and powerful tools to deal with big data nowadays, rather than using mathematical models, the approach of this paper will be via black-box modeling using Long Short-Term Memory (LSTM) Neural Networks (NNs), which has been recently introduced for nonlinear system identification [4, 8].

LSTM is a variant of Recurrent Neural Networks (RNNs), capable of learning long term dependencies, and it overcame the problem of vanishing and exploding gradient that standard RNNs have. In [2] our group presented a new approach to the human lower limb rehabilitation, which assumes a well-mapped relationship (model) between delivered Pulse Width (PW) and knee angular position. The purpose of this paper is to present the application of LSTMs for this task, where it will be evaluated on experimental data from three male healthy subjects. To the best of the authors' knowledge, this NN has never been implemented to this specific application.

The following sections of this paper are organized as: Section 2 presents the theoretical background on system identification with NN and the LSTM method. Section 3 details the instrumentation and experimental set-up for acquiring data. Section 4 presents results, and last, the conclusions and future works are presented in Section 5.

2 Theoretical Background

2.1 System identification via neural networks

Artificial neural networks are based on a collection of inter-connected units named neurons. These neurons are structured into three or more layers, input, hidden(s), and output. Generally, NNs can be divided into two large classes, feed-forward, and recurrent neural networks. On principle, an operator F from an input space $\mathbb{U}$ to an output space $\mathbb{Y}$ expresses the model of the system to be identified. The objective of system identification and modeling is to find a function $\hat{F}$ that approximates F, where, supported by the Stone-Weierstrass theorem, there exists a continuous and bounded function F, that can be uniformly approximated as closely as desired by a polynomial function $\hat{F}$. Additionally, the universal approximation theorem proved that exists a combination of hyper parameters of an NN that allows it to identify any nonlinear function [5, 8].

Consider a single-input and single-output discrete system structure with only the input and output data available as

$$y(k) = f[y(k-1), ..., y(k-n); u(k-1), ..., u(k-m)], \tag{1}$$

where $f(\cdot)$ is an unknown nonlinear difference equation that represents the plant dynamics; u and y are measurable scalar input and output respectively; and m and n are the maximum lags for the system output and input.

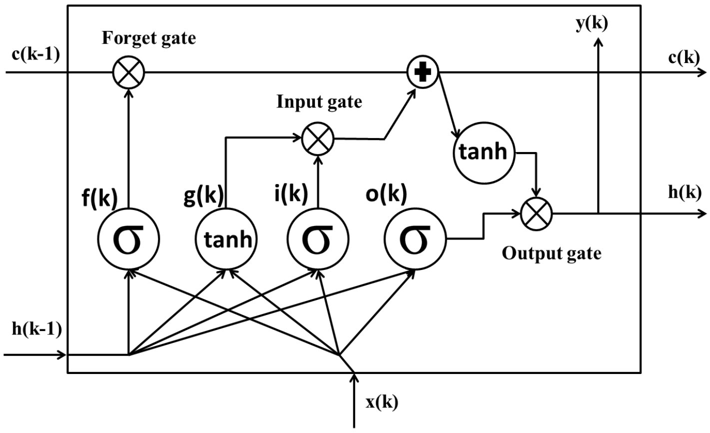
The identification for the discrete-time system in Eq. 1 can be done by following two major types of identification structures presented in the literature as the parallel, and the series-parallel identification model [5]. In this paper, the series-parallel architecture will be implemented, which consists of using both past inputs and system outputs data. This model is always recommended for stability reason and motivated by data availability of past system output. Mathematically this model is described as

$$\hat{y}(k) = F[y(k-1), ..., y(k-n); u(k-1), ..., u(k-m)], \tag{2}$$

where $\hat{y}$ is the model output, y is the real system output, F is the model structure, m and n are the regression order for the input and output. These last two parameters are chosen before the identification process, which n is the output memory to indicate how many past steps of output will be used in the system identification, and m refers to time-step of input values. In this paper, the LSTM is used to approximate the nonlinear mapping function $f(\cdot)$ in Eq. (1), using the series-parallel architecture (Eq. 2) with $m = n = 1$.

2.2 Long short-term memory (LSTM)

Fig. 1 illustrates the inside schematic architecture of the LSTM NN and its mathematical formulation. LSTMs can efficiently learn to maintain information over several time intervals. The essential key behind LSTM success is its memory cell, which divides its states in long-term state $c_{(k)}$ and short-term state $h_{(k)}$. The LSTM cell has a principal layer $g_{(k)}$ and three nonlinear gating units attached, the input $i_{(k)}$, forget $f_{(k)}$ and output $o_{(k)}$ gates, which allows truncating gradients to protect and control the long-term state.



$$i_{(k)} = \sigma(W_{xi}^{T} \cdot x_{(k)} + W_{hi}^{T} \cdot h_{(k-1)} + b_i)$$
$$f_{(k)} = \sigma(W_{xf}^{T} \cdot x_{(k)} + W_{hf}^{T} \cdot h_{(k-1)} + b_f)$$
$$o_{(k)} = \sigma(W_{xo}^{T} \cdot x_{(k)} + W_{ho}^{T} \cdot h_{(k-1)} + b_o)$$
$$g_{(k)} = \tanh(W_{xg}^{T} \cdot x_{(k)} + W_{hg}^{T} \cdot h_{(k-1)} + b_g)$$
$$c_{(k)} = f_{(k)} \otimes c_{(k-1)} + i_{(k)} \otimes g_{(k)}$$
$$y_{(k)} = h_{(k)} = o_{(k)} \otimes \tanh(c_{(k)})$$

Figure 1: LSTM cell and its mathematical formulation

In Fig. 1, $\odot$ means an element-wise multiplication; W_{xi}, W_{xf}, W_{xo} and W_{xg} are the weight matrices of each four layers (principal, input, forget, and output) for their connection to the input vector $x_{(k)}$; W_{hi}, W_{hf}, W_{ho} and W_{hg} are the weight matrices of the same four layers for their connection to the previous short-term state $h_{(k-1)}$; and b_f, b_g, b_i and b_o are the bias terms of each of the previous four layers. The main objective of nonlinear system modeling with LSTM NN is to update the weights between each layer with the input and the short-term state, such that the output $y_{(k)}$ converges to the system output $y(k)$ in Eq. (1).

3 Materials and Methods

3.1 Instrumentation and Analyzed Individuals

Three able-bodied individuals (male, aged 24-28) participated in experiments, in which, this study with volunteers was authorized through a research ethics committee involving human beings (CAAE: 79219317.2.1001.5402) at São Paulo State University (UNESP), and before the participation, written informed consent was obtained from all individuals.

All experiments were performed at the Instrumentation and Biomedical Engineering Laboratory ("Laboratório de Instrumentação e Engenharia Biomédica - LIEB") at São Paulo State University (UNESP) in Ilha Solteira Brazil, using a platform composed of a current-based neuromuscular electrical stimulator; a NI myRIO controller (National Instruments®) to operate in real time; an instrumented chair equipped with an electrogoniometer (Lynx®), a gyroscope LPR510AL (ST Microelectronics®), two triaxial accelerometers MMA7341 (Freescale®); and an user interface developed in the LabVIEW® student version edition.

The neuromuscular electrical stimulator delivers rectangular, biphasic, symmetrical pulses to the individual's muscle, allowing a control adjustment of the PW in $0 - 400\mu s$. Stimulus frequency was fixed in 50 Hz and pulse amplitude in 80 mA. Surface electrodes with rectangular self-adhesive CARCI 50 mm x 90 mm settings were used.

3.2 Data acquisition and experimental procedure

At first, the platform is adjusted for each volunteer to ensure comfort during the tests. Secondly, a muscle analysis is made to determine the motor point and guarantee a proper positioning of the surface electrodes. Then, a few open loop tests are performed applying a step-type signal during four seconds to determine a bounded PW band ($\rho_{min} - \rho_{max}$) concerning to ($\theta_{min} - \theta_{max}$). Subsequently, a small time interval for muscle rest is provided.

Further, five stimulation sessions are carried out with approximately three minutes-time interval for muscle rest. Each session consisted about of two and a half minutes of randomly selected PW in the predetermined range ($\rho_{min} - \rho_{max}$) per individual, applied during minimum four and maximum seven seconds (also random). The motivation to follow this methodology is the attempt to recognize the nonlinear and time-varying nature of muscles and the well-known problem of fatigue via NMES applications during a high time of stimulation.

During the experiments, individuals were instructed to relax and to allow the stimulation to control it. Moreover, individuals could deactivate the electrical stimulation using a stop button, under any displeasure situations.

4 Results and Discussion

The programming language used was Python where several LSTM architectures were tested via a random search procedure until finding the best one and tune its hyperparameters using the Keras library. The best architecture used for all individuals is composed of one single LSTM layer with 271 neurons and a fully connected layer as output, which has one neuron to output the predicted value $\hat{y}$ (model output) with a linear activation function. The batch-learning mode was used with mini-batch size as 64. The Adam optimizer was used with learning rate as 0.0003, and models have trained at most 5000 epochs with an "earlystopping" method of 15 epochs configured to check the Root Mean Squared Error (RMSE) loss function of the validation set, which is a form of regularization to avoid overfitting.

Simulations were performed using data from the first session as training and validation (i.e., considering a patient starting with no data), and all the four remaining ones as testing sets. Thus, Fig. 2 illustrates identification results for all sessions combined (due to page limitations) and for each individual. Additionally, Table 1 presents results regarding the RMSE to all four remaining sessions (from 2nd to 5th) and combined as Total.

Table 1: RMSE for each identification session using the series-parallel architecture.

Individual	**2nd**	**3rd**	**4th**	**5th**	**Total**
H1	0.0290	0.0348	0.0318	0.0454	0.0358
H2	0.0406	0.0694	0.0858	0.1404	0.0913
H3	0.0577	0.0509	0.0858	0.1173	0.0827

Results demonstrated great identification results by following the procedures and models described in this research to the series-parallel configuration. The LSTM NN is an ex-

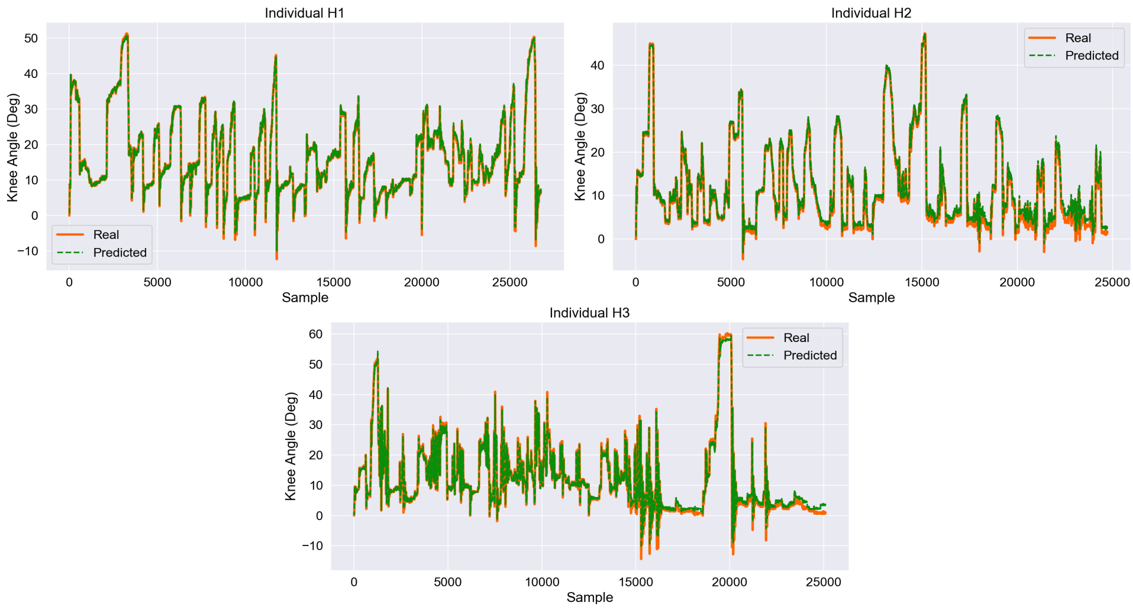


Figure 2: Analysis of LSTM identified models for each individual.

cellent tool for sequential and time-series data as reported in the literature, which makes it ideal to identification of knee joint under NMES. As Table 1 and Figure 2 showed, results with just one time-step ($m = n = 1$) are already very accurately, and we believe that by concentrating more efforts trying more architectures and more time steps, results can improve even more.

RNNs are easier to train in comparison with mathematically modeling the knee joint dynamics and executing tests for identifying parameters of each individual. Focusing more efforts on the model selection procedure could provide stronger models for input-output data modeling. Hence, using an appropriate choice of architecture and hyperparameters, the modeling of such dynamics would not be difficult for such LSTM NNs, as demonstrated in Figure 2.

5 Conclusion

The identification of knee joint dynamics under the application of NMES has been addressed for three healthy male subjects using LSTM NNs in this paper. The behavior of a dynamic system can be described as special time-series problems, whereby using an RNN in which there is a self-feedback of neurons in the hidden layer(s) it provides the ability to use contextual information when mapping between input and output sequences. Therefore, using the series-parallel structure, the LSTM could identify highly accurately the knee angular position due to the electrical stimulus for all three individuals, proving to be a prospective method for deeper investigation on nonlinear system identification and modeling.

For future work, it is planned the real implementation of LSTMs on control-oriented models to the knee joint using NMES, and the combination of LSTMs with other NN models, e.g., the convolutional NN.

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References

[1] T. Anwar, Y. M. Aung and A. A. Jumaily, The estimation of Knee Joint angle based on Generalized Regression Neural Network (GRNN), IEEE International Symposium on Robotics and Intelligent Sensors (IRIS), (2015), DOI: 10.1109/iris.2015.7451613.

[2] H. H. Arcolezi, W. R. B. M. Nunes, S. L. C. Ñahuis, M. A. A. Sanches, M. C. M. Teixeira and A. A. de Carvalho, A RISE-based Controller Fine-tuned by an Improved Genetic Algorithm for Human Lower Limb Rehabilitation via Neuromuscular Electrical Stimulation, 6th International Conference on Control, Decision and Information Technologies (CODIT), (2019).

[3] M. Ferrarin and A. Pedotti, The relationship between electrical stimulus and joint torque: a dynamic model, IEEE Transactions on Rehabilitation Engineering, vol. 8, 342–352, (2000), DOI: 10.1109/86.867876.

[4] J. Gonzalez and W. Yu, Identification and control of dynamical systems using neural networks, IFAC-PapersOnLine, vol. 51, 485–489, (2018), DOI: 10.1016/j.ifacol.2018.07.326.

[5] K.S. Narendra and K. Parthasarathy, Identification and control of dynamical systems using neural networks, IEEE Transactions on Neural Networks, vol. 1, 4–27, (1990), DOI: 10.1109/72.80202.

[6] F. Previdi, Identification of black-box nonlinear models for lower limb movement control using functional electrical stimulation, Control Engineering Practice, vol. 8, 91–99, (2002), DOI: 10.1016/s0967-0661(01)00128-9.

[7] R. Riener, J. Quintern and G. Schmidt, Biomechanical model of the human knee evaluated by neuromuscular stimulation, Journal of Biomechanics, vol. 29, 1157–1167, (1996), DOI: 10.1016/0021-9290(96)00012-7.

[8] Y. Wang, A new concept using LSTM Neural Networks for dynamic system identification, American Control Conference (ACC), (2017), DOI: 10.23919/acc.2017.7963782.