ARGESIM COMPARISONS

Identification of Nonlinear Dynamics – Neural Networks versus Transfer Functions - Definition of a New ARGESIM Comparison - C18

Aleš Belič, ales.belic@fe.uni-lj.si

University of Ljubljana, Faculty of Electrical Engineering, Laboratory of Modelling, Simulation and Control (LMSC), Trzaška 25, 1000 Ljubljana, Slovenia

This comparison studies alternative approaches for identification of the nonlinear dynamical relation between muscle force and muscle-belly thickening. Classical transfer function models and as alternative neural net models are to be compared.

The system is animal skeletal muscle, and measured are muscle-belly thickening, and muscle force. The aim is to identify a relation between the two measured signals in order to show that the two signals are related to each other.

The motivation for the study is the fact that muscle force cannot be measured non-invasively; therefore, an indirect non-invasive measurement is necessary to characterize the muscle force. Many muscle and nervous diseases manifest themselves in reduced muscle force or slowed-down muscle contraction/relaxation dynamics. The muscle force observations can also be used as a measure for athlete's condition. A possible marker for muscle force could be muscle-belly thickening measurements.

If a mathematical model can be composed that would take muscle-belly thickening as the input and would calculate the muscle force on the output then the relation between the two measurements exists and muscle-belly thickening measurements can serve as a marker for muscle-force.

Measured data characterisation.

Two data sets, measured on the same muscle type (gastrocnemius) taken from two toads (*bufo bufo*), were used in this comparison (see Figure 1 and Figure 2).

The data set from the first muscle is used for identification procedures and the data set from second muscle is used for validation purposes.

First, the data is filtered with low-pass filter and resampled at 100Hz sampling frequency to reduce the noise and to reduce the amount of data. Next, the data is characterized for dynamic/static properties using the phase plot (see Figure 3 and Figure 4).

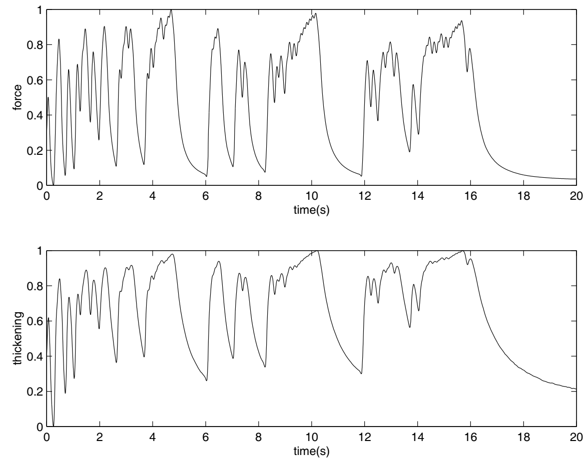

Figure 1: Measured thickening and force, first muscle.

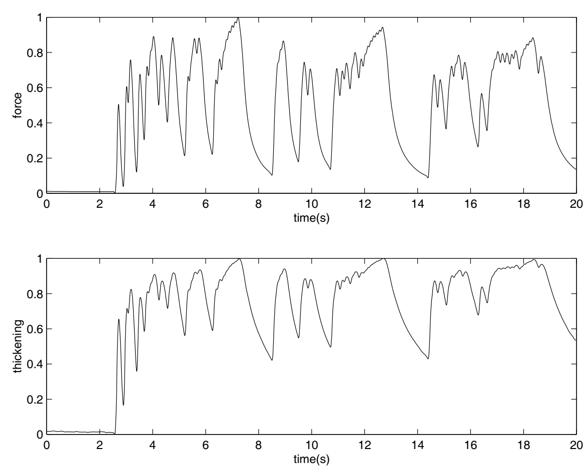

Figure 2: Measured thickening and force, second muscle.

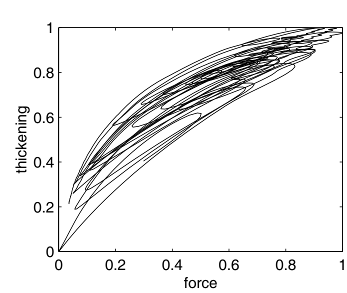

Figure 3: Phase plot of muscle-force and muscle-belly thickening for training data set.

In Figure 3 and Figure 4 irregularly shaped loops can be observed, which implies on non-linear dynamical system, therefore, a dynamical model should be composed.

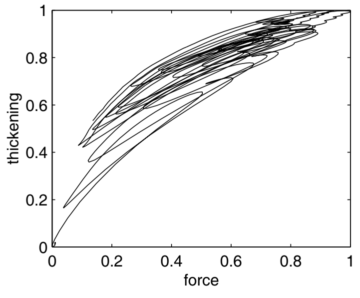

Figure 4: Phase plot of muscle-force and muscle-belly thickening for validation data set.

Task a: Identification with discrete linear dynamical model

First, identification with linear dynamical model (see Figure 5) should be tried.

Although, the analysis above suggests that the relation is non-linear, a linear model is always helpful for the analysis of the general properties of the relation.

As the system can be described as mechanical system that includes moving masses, second order model should be used with least-squares identification method.

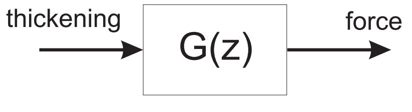

Figure 5: Identification with discrete linear model. G(z) represents discrete transfer function.

Task b: Identification with linear dynamical model and artificial neural network (ANN) in parallel

The relation between muscle-belly thickening and muscle force can also be identified with parallel structure as seen in Figure 6. The difference between the simulated force, using dynamical linear model, and real system's measured response can be modelled with the ANN.

Thus a more precise prediction can be obtained. Discrete linear model covers the dynamical properties of the system, whereas the ANN covers the non-linear characteristics.

The proposed structure is useful when modelling dynamical and non-linear systems where linear models are not providing the prediction that is accurate enough, and ANN training algorithms have problems with training of the dynamical ANN structures due to the high complexity of the ANN.

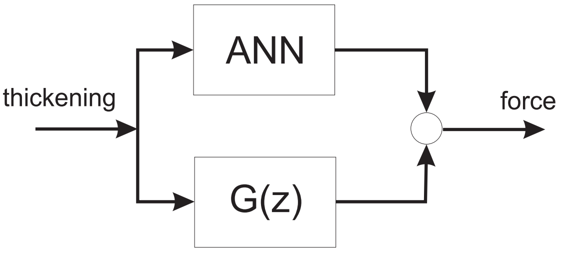

Figure 6: Discrete linear dynamical model in parallel with the ANN.

First, the linear dynamical model is identified with the least square method, than the ANN is trained to simulate the difference between the linear model simulation and real systems response.

Task c - Identification with a dynamical ANN

A dynamical ANN can be used to solve the problem as well (see Figure 7).

Figure 7: A neural network model.

In this case, the ANN's task is to cover the system dynamics as well as the non-linearity. The procedure is simpler than with the hybrid model, however, the training of the network is far more time consuming.

The structure of dynamical ANN is more complex than the one of static ANN, due to internal feedbacks, and repetitions of training do not necessary provide the same prediction quality of the ANN. Therefore, it is necessary to repeat the training several times, to obtain optimal results, which is time consuming.

Solutions: Clearly, this comparison addresses software, which is able to handle neural nets and / or model identification. The sample solution is implemented in MATLAB, using all necessary toolboxes, so that this solution is an easy solution. Nevertheless solutions using general purpose simulators or other CACSD tools are expected. Measured data to be used in this comparison can be downloaded from the ARGESIM webpage, where also this definition can be found.

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