EMG based prediction of upper limb intention of motion using a combination of non-linear auto-regressive models

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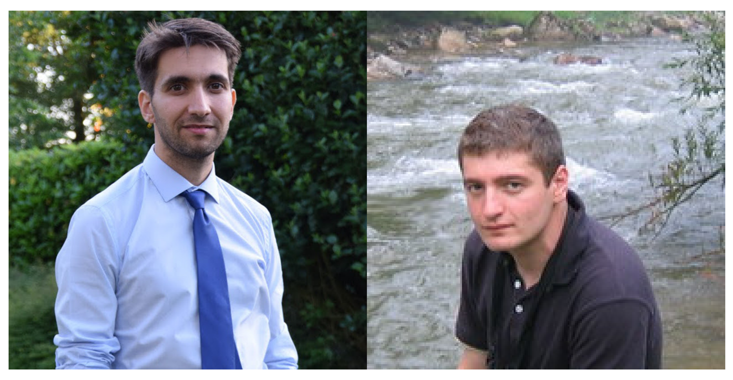


Robotics & Non-linear Control

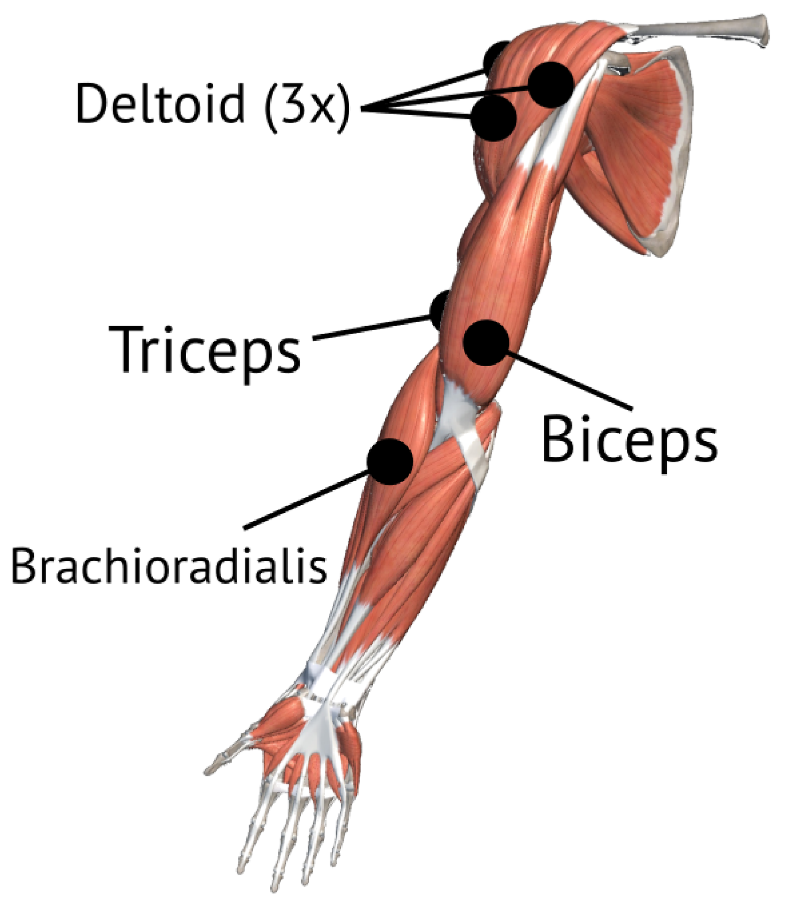
Motivation

For any application that requires the human-robot collaboration to be safe, there has to be clear communication about the intentions of each side. While the intentions of the robot can be communicated to the human through screens or indicators incorporated in the robot, the intention of humans is more difficult to be communicated to the robot in a timely and concise manner, especially when dealing with upper-limb motion. Therefore, an automatic detection of the intention is preferable.

Several approaches have been used to detect and predict human upper-limb intention, the majority of them involving either direct observation of arm kinematics or measurement of biological signals relating to motion, such as Electromyography [1, 2] (EMG), or Electroencephalography [3, 4] (EEG). While the EEG signals can in principle provide lower-level information of intention, it is generally difficult to record and decode. Therefore, the EMG signal has been used more extensively for prediction studies. EMG signals are also more preferred than kinematics, as they provide information on the motion that is about to occur a few milliseconds before it actually initiates, enhancing therefore the prediction horizon of the intention.

In this work, we present a combination of two non-linear auto-regressive [5] (NAR) models (one of them being exogenous NARX [6]), for the prediction of EMG signals and of the resulting upper-arm kinematics. The models are implemented using shallow neural networks. The NAR model is used to predict the EMG signals in the near future, using trajectories for the kinematics and the EMG signals. The NARX model uses the EMG prediction to calculate the resulting kinematics of the upper arm during the prediction horizon. The models are able to predict reliably the EMG signals and the resulting kinematics during the chosen prediction horizon (1 sec) when trained for specific rehabilitation related motions.

Kinematics and EMG measurements



The six muscles measured during the acquisition

For training and validating our models, we performed measurement of kinematics and EMG activation with volunteers.

- 8 healthy volunteers (5 male, 3 female, average age 32.3, range 23-40 years old)
- Three types of motion (elbow flexion-extension, arm raising, arm crossing)
- 10 repetitions, three trials for each volunteer

The kinematics were captured:

- Astra Pro depth camera (Orbbec, Shenzhen, Guangdong, PRC)
- Acquisition at 40 Hz
- Converted skeleton data into joint angles using inverse-kinematics [7]

For the EMG:

- Considered six muscles
- Non-polizable silver-silver chloride electrodes
- Acquisition using a NI-9205 module (National Instruments)
- Signals filtered according to literature [8]
- Activation quantified based on root mean square (RMS)

Neural network architecture

- Two neural networks for each participant and type of motion
- Six EMG signals and four joint trajectories as inputs
- First network was a Nonlinear auto-regressive model, predicting the EMG trajectory (NAR)
- Second network was a Nonlinear auto-regressive exogenous model, predicting the resulting kinematics (NARX)
- Each network 2 layers deep, with 5 neurons on the hidden layer
- Two trials used for training, one for validation

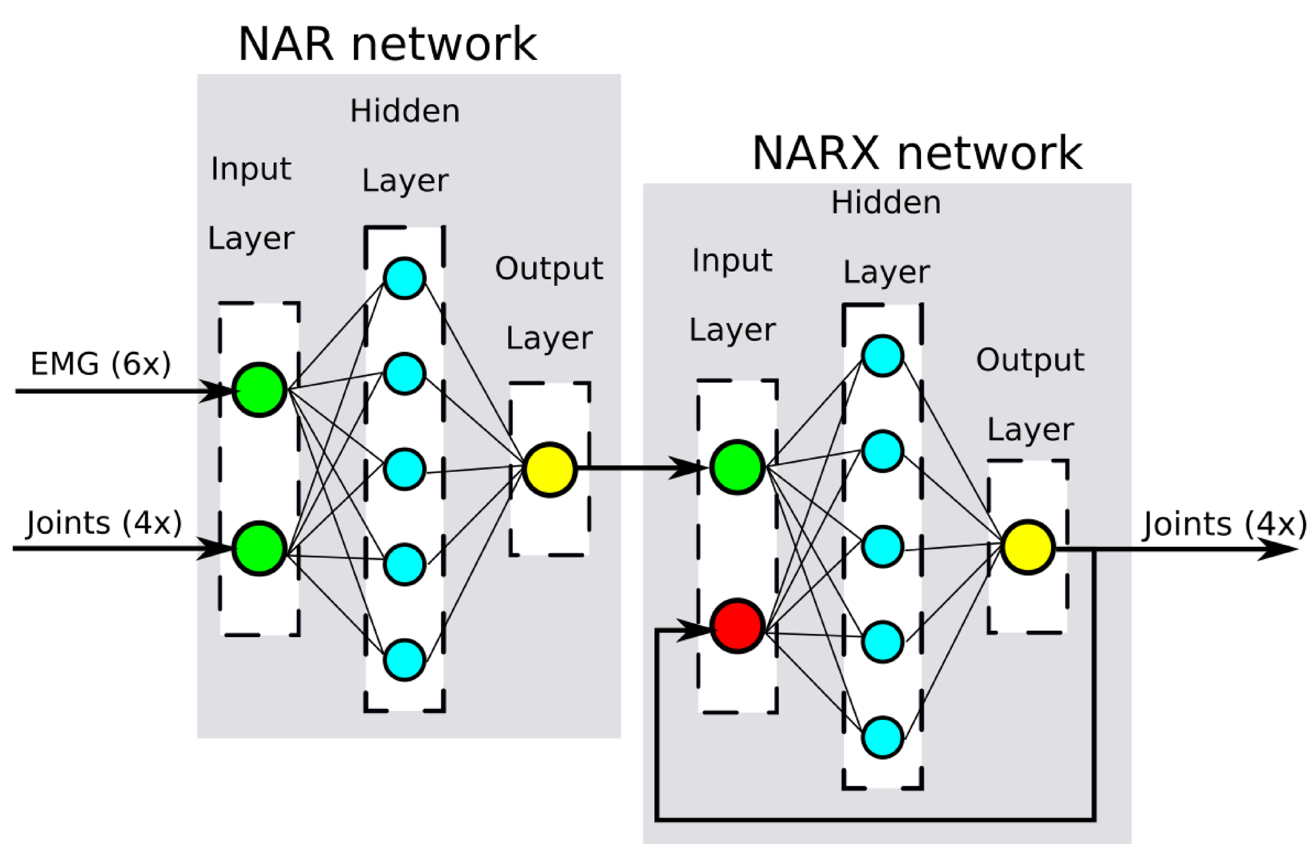
The two networks were constructed and trained using the neural network toolbox of MATLAB (Mathworks, Natick, MA). Once both neural networks were trained, they were coupled together so that the output of the NAR network (the EMG part) was the exogenous input of the NARX network. The models were run to predict the EMG and afterwards the joint angles for a period of 1 second. The RMS between the output of the NARX network (joint angles) and the values from the actual measurement was calculated.

Results

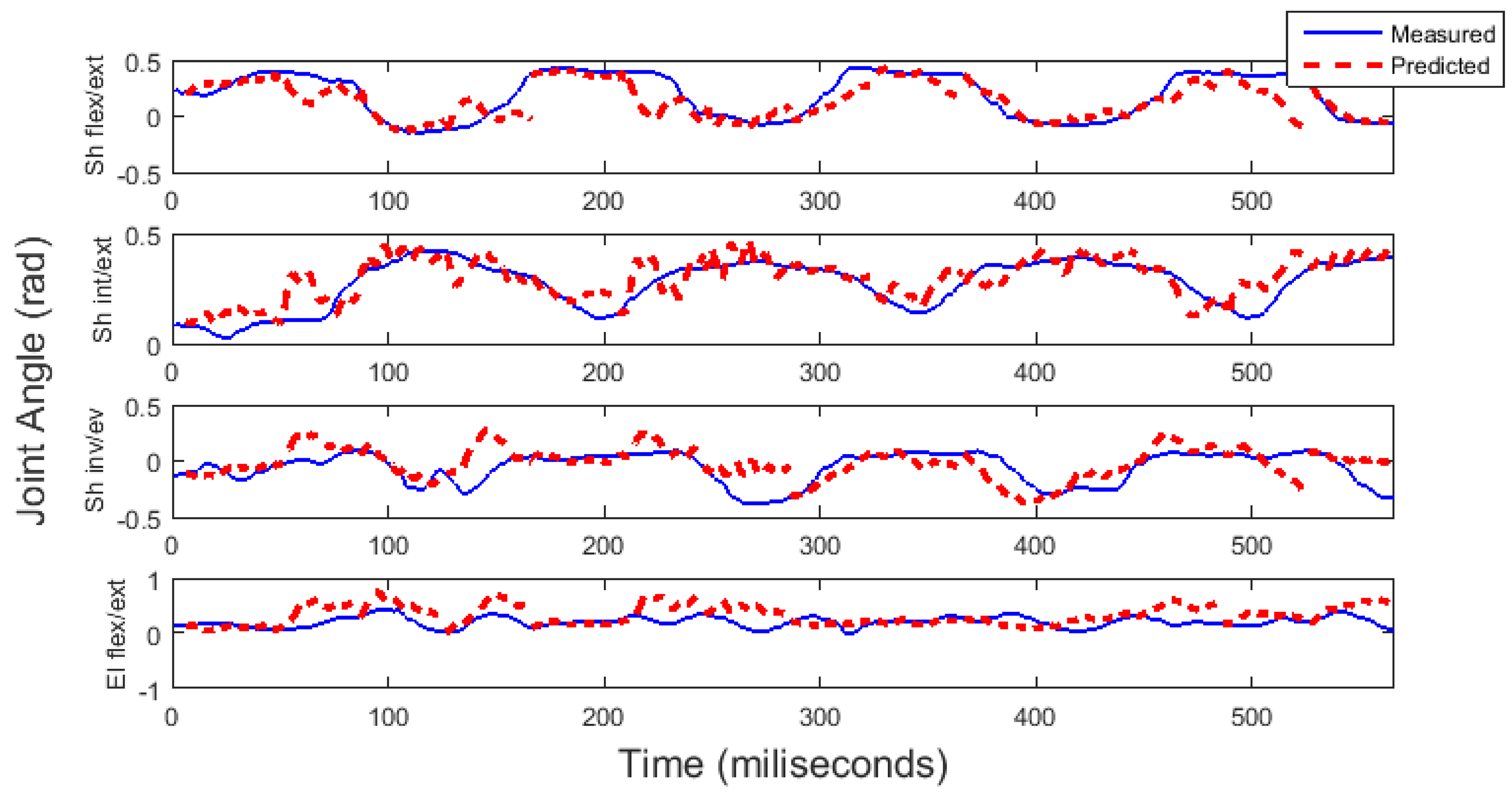
The worst case RMS calculations for each participant and each type of motion are presented in Table 1. The least performing case was for participant 8 and 'Arm raise' type of motion, with an RMS value of 2.0188. A sample of the prediction is presented in Figure 1 (participant 7, elbow flexion).

Conclusions

In this work, we demonstrated the performance of two non-linear auto-regressive models, implemented using neural networks, combined to form a more complex model that predicts upper-limb motion on a horizon of one second. This prediction uses only previously collected information on EMG and kinematics and could be utilized in applications needing intention of motion, and is especially useful when a relatively long prediction horizon is needed. This can be the case in rehabilitation robotics, where a long prediction horizon can assist in the motion planning of the robot. The future steps from this work will be to include more types of motion, and to couple the prediction with a motion classification network. By classifying the type of motion, the algorithm will be able to select the corresponding prediction network which will increase the efficiency of the prediction.



Architecture of the NAR and NARX networks. The first network is run for predicting the future values of the EMG signals using only past values. The output of the first network is fed as an input for the second network, which predicts the resulting kinematics based on the predicted EMG signals.



Comparison of measured (blue) and predicted (dotted red) joint angles over time. The prediction is performed every one second for the next one second. The prediction is performed for the four joints (Shoulder flexion-extension, Shoulder internal-external rotation, Shoulder inversion-eversion, and Elbow flexion-extension).

Total RMS between actual and predicted joint angles over time, for all four joints.

Motion	Participants							
	1	2	3	4	5	6	7	8
Elbow flexion	0.3493	0.2902	0.2845	0.2403	0.2929	0.2984	0.2587	0.3925
Arm raise	0.3406	0.8447	1.4765	1.4041	0.7518	0.6603	0.8220	2.0188
Arm cross	0.1885	1.5351	0.2790	0.7330	0.9747	0.5763	0.5466	0.7362

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