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

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1. INTRODUCTION

With the advent of robotics, the opportunity to use robots in the vicinity of humans has emerged. Human-robot collaboration is a rapidly developing field for industrial applications, but can also have significant impact on healthcare related applications, such as robotic assisted surgery or robotic rehabilitation. 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.

Most current research has been focused on calculating the resulting motions once the EMG has been recorded, using either traditional modeling approaches (kinematics [5], dynamical [6] or musculoskeletal [7] modeling), or model-free approaches using artificial intelligence algorithms. However, little research has been performed on predicting the EMG signals themselves using knowledge only from the history of the EMG signals.

In this work, we present a combination of two non-linear auto-regressive (NAR) models (one of them being exogenous NARX), 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.

2. METHODS

2.1. Kinematics and EMG measurements

8 healthy volunteers (5 male, 3 female, average age 32.3, range 23-40 years old) were recruited to participate in developing and training the prediction models. The participants were asked and gave their informed consent about participating in the measurements. Each participant was asked to perform three types of motion, all relating to a rehabilitation task (elbow flexion-extension, arm raising, arm crossing). Each motion was performed 10 times for each trial, and for each participant three trials were performed. The motions were performed at a self-selected speed and range of motion.

During the motions, the kinematics of the upper arm were captured using an Astra Pro depth camera (Orbbec, Shenzhen, Guangdong, PRC) at 40 Hz. The skeleton data were converted into joint angles using an inverse-kinematics model of the upper arm [5], resulting in four angles (three angles for the shoulder and one for the elbow). The muscle activation of six muscles of the upper arm (Anterior, Lateral, and Posterior deltoids, Biceps, Triceps, and Brachioradialis) was measured simultaneously using non-polarizable silver-silver chloride (Ag/AgCl) electrodes. The signals from the electrodes were captured using a NI-9205 module (National Instruments, Austin, TX) and were further processed in LabVIEW 2017 (same developer). The signals were processed according to literature [8] with a band-pass (20-500 Hz) and a subsequent band-stop (45-55 Hz) filter. Finally the muscle activation was quantified using the root mean square (RMS) of the filtered signal.

2.2 . Neural network training

Two neural networks were developed and trained for each participant and for each type of motion. The measurements from the first two trials were used for training, while the last trial was used for determining the performance of the model. The first neural network was a non-linear auto-regression model, and was used for prediction of the EMG signals of the six muscles. To train the model, both the data of the EMG and of the kinematics were used as independent signals. This was done to increase the accuracy of the model, since the kinematics provide extra information on the state of the arm at every timestep. The network was two layers deep consisting of a hidden layer of five neurons and an output layer of 10 neurons. The input layer was also consisting of 10 neurons (6 for the EMG signals, 4 for the joints).

The second network was a non-linear auto-regression exogenous model. The exogenous input of the model was chosen to be the EMG signals while the output was chosen to be the joint angles. The size of the NARX network was the same as the NAR one.

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.

3. 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).

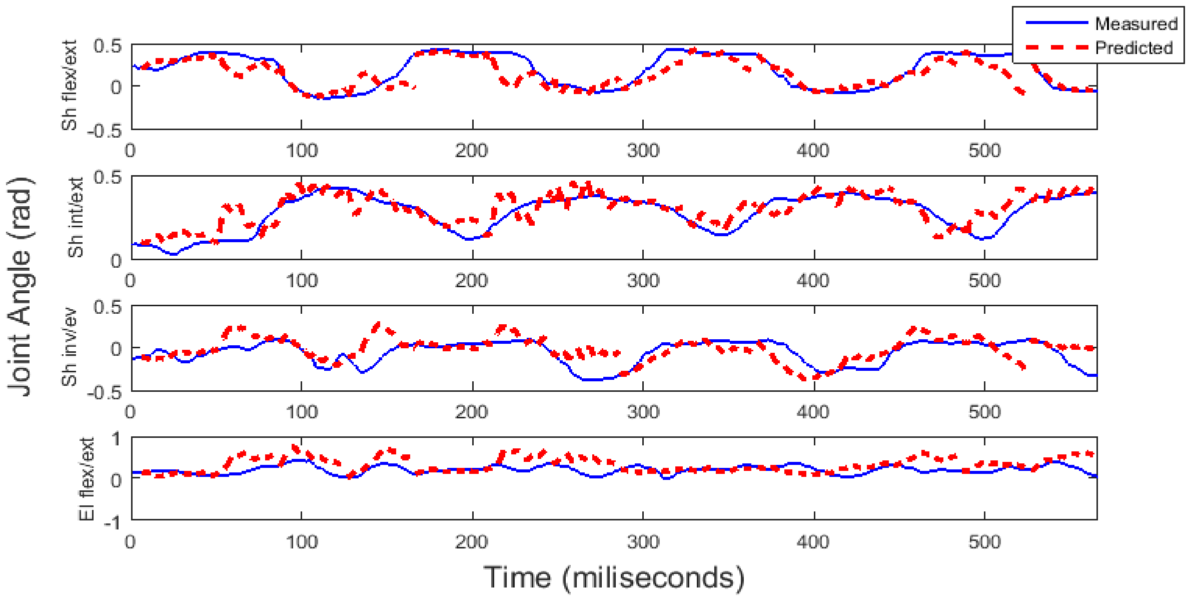

Fig. 1 Comparison of measured (blue) and predicted (dotted red) joint angles over time. The prediction is performed every one second for the next one second. The prediction is performed for the four joints (Shoulder flexion-extension, Shoulder internal-external rotation, Shoulder inversion-eversion, and Elbow flexion-extension).

Table 1. Total RMS between actual and predicted joint angles over time, for all four joints.

	PARTICIPANT							
	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

4. CONCLUSION

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.

References

[1] J. Liu, S. H. Kang, D. Xu, Y. Ren, S. J. Lee, and L.-Q. Zhang, *EMG-Based Continuous and Simultaneous Estimation of Arm Kinematics in Able-Bodied Individuals and Stroke Survivors*, Front. Neurosci., **11**, (2017).

[2] Y. M. Aung and A. Al-Jumaily, *Estimation of Upper Limb Joint Angle Using Surface EMG Signal*, International Journal of Advanced Robotic Systems, **10**, 369, (2013).

[3] J. Zhou, J. Yao, J. Deng, and J. P. A. Dewald, *EEG-based classification for elbow versus shoulder torque intentions involving stroke subjects*, Computers in Biology and Medicine, **39**, 443–452, (2009).

[4] S. Yousefizadeh, J. de D. Flores Mendez, and T. Bak, *Trajectory adaptation for an impedance controlled cooperative robot according to an operator's force*, Automation in Construction, **103**, 213–220, (2019).

[5] B. J. Borbély and P. Szolgay, *Real-time inverse kinematics for the upper limb: a model-based algorithm using segment orientations*, BioMedical Engineering OnLine, **16**, 21, (2017).

[6] E. A. Clancy, L. Liu, P. Liu, and D. V. Z. Moyer, *Identification of Constant-Posture EMG–Torque Relationship About the Elbow Using Nonlinear Dynamic Models*, IEEE Transactions on Biomedical Engineering, **59**, 205–212, (2012).

[7] Lin Wang and T. S. Buchanan, *Prediction of joint moments using a neural network model of muscle activations from EMG signals*, IEEE Transactions on Neural Systems and Rehabilitation Engineering, **10**, 30–37, (2002).

[8] Marco Barbero, *Atlas of Muscle Innervation Zones - Understanding Surface Electromyography and Its Applications,* Springer.

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