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Predicting Intention of Motion During Rehabilitation Tasks of the Upper-Extremity

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Abstract— **Rehabilitation promoting "assistance-as-needed" is considered a promising scheme of active rehabilitation, since it can promote neuroplasticity faster and thus reduce the time needed until restoration. To implement such schemes using robotic devices, it is crucial to be able to predict accurately and in real-time the intention of motion of the patient. In this study, we present an intention-of-motion model trained on healthy volunteers. The model is trained using kinematics and muscle activation time series data, and returns future predicted values for the kinematics. We also present the results of an analysis of the sensitivity of the accuracy of the model for different amount of training datasets and varying lengths of the prediction horizon. We demonstrate that the model is able to predict reliably the kinematics of volunteers that were not involved in its training. The model is tested with three types of motion inspired by rehabilibation tasks. In all cases, the model is predicting the arm kinematics with a Root Mean Square Error (RMSE) below 0.12m. Being a non person-specific model, it could be used to predict kinematics even for patients that are not able to perform any motion without assistance. The resulting kinematics, even if not fully representative of the specific patient, might be a preferable input for a robotic rehabilitator than predefined trajectories currently in use.**

Clinical relevance- **This model predicts intention of motion for use as a setpoint for robotic rehabilitators. This can be useful for patients that are not able to perform motions without assistance.**

I. INTRODUCTION

In the past two decades, robots have frequently been used for assisting rehabilitating patients, either to promote neuroplasticity after a stroke, or to re-train muscles after an accident or trauma. The benefits of using robots for rehabilitation are numerous: patients can recover faster, clinics can treat more patients, and physiotherapists do not need to support the heavy burden of assisting patients. However, robotic rehabilitation has not reached maturity in the clinical setting yet.

Two of the most prominent solutions for robotic rehabilitation are exoskeletons and end-effector devices[1]. Exoskeletons allow a vast variety of motions with a device that shares the joint space of the human structure that is rehabilitated[2]. End-effector devices on the other hand offer assistance for a limited type of motions, but are cheaper to develop and maintain. A third solution that is yet to be explored is the use of robotic arms. Collaborative robotic arms have been proven safe to be used in close proximity with humans [3], and can offer a large number of benefits. First of all, there is no development cost as they can be acquired off the shelf. The set up time is minimal when used in rehabilitation, as they require a single point of attachment with the patient. Nevertheless, they provide a high degree of flexibility of motions that are supported for rehabilitation.

The main challenge of using robotic arms for rehabilitation is the complexity in calculating the trajectory that must be executed by the robot. This would be relatively simple to resolve in passive rehabilitation schemes, where the robotic device drives the motion and no participation from the patient is necessary. However when active participation from the patient is needed, the robotic rehabilitator must have an indication of the intention of motion of the patient. Furthermore, this intention of motion must be calculated and communicated to the robot in real-time, so as to allow the robotic arm to calculate trajectories along the intended motion and to then assist the patient in executing them.

Several studies have been performed in calculating the intention of motion from various biological signals, such as Electromyography (EMG) [4], [5], [6], Electroencephalography (EEG) [7], [8], or a combination of EMG and kinematics [9]. However, all of these studies are subject-specific and require training data for each patient. While this might be sensible in some situations, it is not an option when performing rehabilitation in patients where there is e.g. muscle activation that does not produce motion, as there is no way to generate the motion training data.

To alleviate this hindrance, we are presenting a generic intention of motion model for predicting the upper arm kinematics during rehabilitation tasks. The model is based on simultaneous measurements of the EMG and kinematics and is able to predict the intention of motion in real-time with a variable prediction horizon. This model is trained with data collected from five healthy volunteers performing three different types of motion. The model could predict the kinematics of volunteers that have not been used for training, making it therefore possible for use with patients that are unable to perform motions. Even if this prediction is not fully representative of the actual intention of the patient, it is likely to be a more suitable input for a robotic rehabilitator than the predefined trajectories that are currently used.

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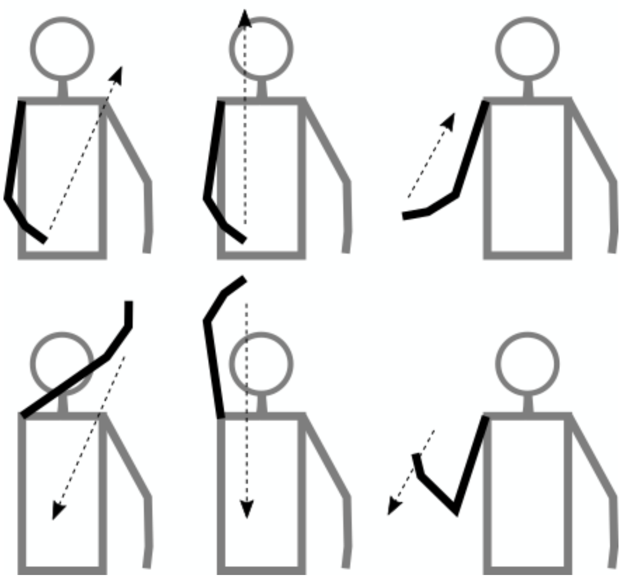

Fig. 1. The three types of motion performed by volunteers. On the top row is the starting position, on the bottom the ending position. The first motion was scapular anterior elevation/posterior depression (arm cross), the second scapular anterior depression/posterior elevation (arm raise), while the third was elbow extension/flexion (elbow flexion).

II. METHODS

A. Data acquisition

5 healthy volunteers (4 male, 1 female, average age 32.2, range 24-39 years old) were recruited to participate in developing and training the prediction models. The protocol of this study was approved by the Ethics Committee of the Technical University of Cluj-Napoca (no. 163/22.01.2020), where the study took place. The participants were provided with an informed consent form prior to the experiments, and were asked to sign it at the beginning of the measurements. All the aspects of this study were in accordance to the principles of the Declaration of Helsinki. Each participant was asked to perform three types of motion, promoting proprioceptive neuromuscular facilitation (PNF) [10]: scapular anterior elevation/posterior depression (arm cross), scapular anterior depression/posterior elevation (arm raise), and elbow extension/flexion (elbow flexion) (Figure 1). Each participant performed each motion 10 times in a continuous manner for each trial, for three trials in total. This was repeated for each type of motion separately. 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. Using the Software Developers Kit (SDK) provided by the manufacturer, we extracted skeleton data representing the position of various joint segments and joints in three dimensional space. The arm kinematics were decomposed into joint angles using an inverse kinematics calculation. Three joints were considered at the level of the shoulder (Abduction/Adduction, Extension/Flexion, Internal/External rotation) and one at the level of the elbow (Extension/Flexion).

For the muscle activation, we selected six muscles of the upper arm (Anterior, Lateral, and Posterior deltoids, Biceps, Triceps, and Brachioradialis) that are the major contributors to the motions of the shoulder and elbow. The muscle activation of these muscles was measured simultaneously using non-polarizable silver-silver chloride (Ag/AgCl) electrodes. Two electrodes were attached on each muscle at appropriate locations to avoid muscle innervation-zones [11]. The differential voltage from each pair of electrodes was captured using a NI-9205 module (National Instruments, Austin, TX) at 20 kHz. The signals were further processed in LabVIEW 2017 (same developer) according to the literature [11] 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 every 500 samples, producing values for muscle activation at 40 Hz.

The kinematics and muscle activation were captured independently, but using the same computer. A timestamp was recorded for each signal, which was used during post-processing for synchronising and aligning the signals.

B. Model structure, training, and validation

For predicting the intention of motion we constructed a neural network model based on Long Short-Term Memory (LSTM) layers [12]. This type of layer was selected because of its applicability in multivariate time-series forecasting [13], [14]. The structure of the network had 3 hidden layers, with 20, 150, and 20 LSTM nodes respectively. The model received as input a tensor of size 10×10 which represented the ten input signals (six muscle activations and four joint angles), each signal having 10 delay states (past values). The output layer had $4 \times n$ nodes, representing the four output signals (joint angles) for n time steps (prediction horizon) (see Figure 2). A sensitivity analysis was performed to study the accuracy of the model for different lenghts of the prediction horizon and using different amount of subjects as training data (see Figure 3 and the related discussion).

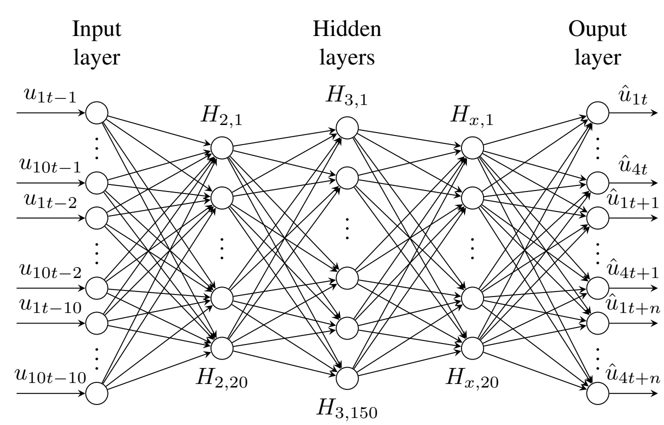

Fig. 2. Structure of a time-delay multivariate neural network. The input layer has one node for each previous timestep (10) of each of the 10 variables (muscle activation and joint angles). The output layer has n nodes for each of the 4 prediction variables (joint angles), representing the prediction for the following n timesteps.

For training the model, we implemented a k-1 approach for each type of motion. The data from four volunteers were used to train the network, which was then used to predict the kinematics of the fifth volunteer. The training set of volunteers was then rotated and the model was retrained from the beginning, using the remaining volunteer for validation. We therefore performed five validations for each type of motion using different training and validation sets. Each training and validation was repeated 10 times, using random initial weights, to remove potential biases in the results.

The metric used for the validation was the root mean square error of a sequential prediction over the whole duration of a trial. The prediction was first performed using the first 10 samples for the next n samples, and was then shifted by n samples each time until the end of the trial. The overall root mean square error (RMSE) from beginning until the end of the validation trial was quantified for all four joint angles.

C. Sensitivity analysis

To demonstrate the accuracy of model under varying lengths of the prediction horizon and different sizes of the training datasets, we performed a sensitivity analysis, where the model was trained as explained above for various values of n (prediction steps) and m (number of subjects used for training). The number of timesteps of the prediction horizon n took a value from the set $[10, 20, 30, 40, 50, 60, 70, 80]$, while the number of persons used for the training m took a value from the set $[1, 2, 3, 4]$. For each combination of n and m, the models were trained 10 times, using random initial weights, to remove potential biases in the results.

III. RESULTS

The results of the sensitivity analysis are presented in Figure 3. Based on these results, the necessary number of subjects used for training m can be determined for the required prediction horizon (n) and prediction accuracy. As expected, the accuracy of the model degrades with a longer prediction horizon, and it increases with a larger number of training subjects.

The specifications for our application dictated a prediction accuracy of 0.12m, which allowed a prediction horizon of $n = 20$ samples using 4 subjects for training. This prediction horizon corresponded to 0.5 seconds, since the data had a sampling rate of 40Hz. To demonstrate the performance of the model under these conditions, we present a training and validation trial in Figure 4 and Figure 5 respectively. The summary statistics for the RMSE are presented in Figure 6 and Table I. The median RMSE for the training sets is 0.07, 0.07, and 0.03 m for each type of motions respectively, while for the validation sets is 0.12, 0.11, and 0.09 m for each type of motion respectively.

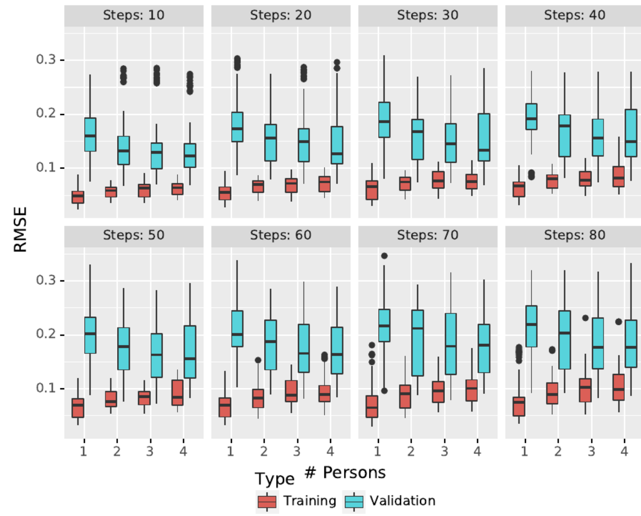

Fig. 3. Sensitivity of prediction accuracy on the number of predicted steps (prediction horizon). The accuracy for the training (blue) and validation (red) set is presented in a boxplot. Each boxplot is describing the distribution of RMSE over the 10 iterations for all the subjects. The height of each box represents the interquartile range, while the bottom and top end of the whiskers represent the lowest and highest value still within 1.5 of interquartile ranges respectively. The horizontal line inside the box represents the median. The dots represent measurements outside 1.5 of interquartile range and are considered outliers.

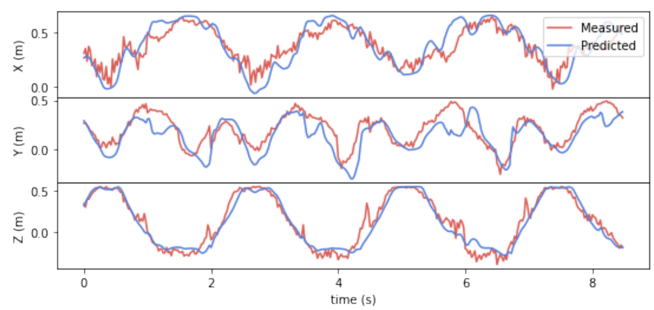

Fig. 4. Training trial, with measured (red) and predicted (blue) kinematics. The kinematics of the hand for the X, Y, and Z coordinates are presented over time

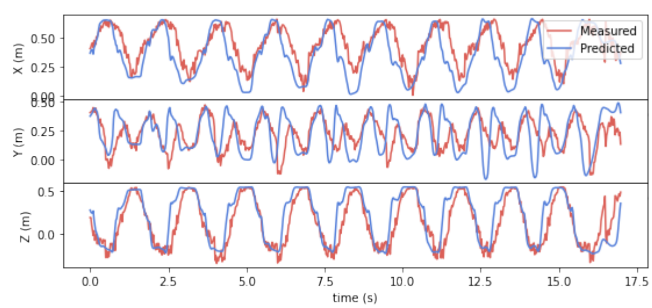

Fig. 5. Validation trial, with measured (red) and predicted (blue) kinematics. The kinematics of the hand for the X, Y, and Z coordinates are presented over time

IV. DISCUSSION & CONCLUSION

In this study, we presented a methodology for predicting accurately and repeateadly upper-extremity kinematics of healthy volunteers, using a generic model based on an LSTM neural network. This is possible through simultaneous measurement of muscle activation and kinematics, and the model is able to predict future kinematics in real-time. It is

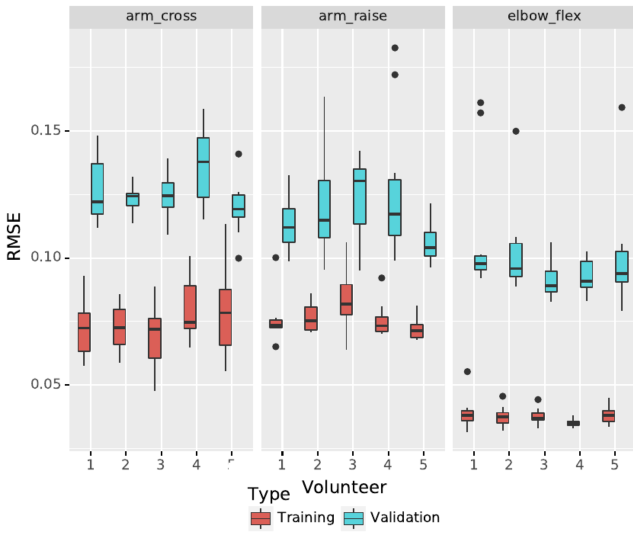

Fig. 6. Summary of the RMSE values for each kind of motion (arm cross, arm raise, elbow flex), and each validating volunteer. A boxplot is representing the distribution of the training (blue) and validation (red) trials.

TABLE I

SUMMARY STATISTICS OF THE RMSE VALUES FOR EACH KIND OF MOTION AND VALIDATING VOLUNTEER. ALL VALUES ARE IN METERS.

		RMSE			
		min	max	median	std
Kind	Type				
arm_cross	Training	0.047	0.113	0.073	0.013
	Validation	0.099	0.158	0.123	0.012
arm_raise	Training	0.063	0.106	0.073	0.008
	Validation	0.095	0.182	0.112	0.018
elbow_flex	Training	0.031	0.055	0.036	0.004
	Validation	0.079	0.161	0.094	0.018

therefore fitting to be used in robotic rehabilitation studies that need to provide "assistance-as-needed". A sensitivity analysis is presented for defining the necessary number of training subjects for the desired prediction horizon and prediction accuracy.

The accuracy of the model for the selected prediction horizon is less than 0.1m for most types of motion, which is deemed sufficient for our specific application. The accuraccy of the prediction for the "arm raise" and the "arm cross" type of movement is considerably lower than that of the "elbow flex" motion. This is probably due to the higher complexity of the motions, involving a larger range of motion for all four joints of the arm. However, if higher accuracy is necessary for some types of motion, this can be achieved either by decreasing the horizon of the prediction, or by including more training data. Ideally, the model should be trained with a more extensive population, on a wider age range, higher gender balance, and possibly different anthropometric characteristics.

The model has only been tested in a healthy population, however the intention is to use this model in patients thare are in need of rehabilitation. This will be possible with patients that do have muscle activation but are not necessarily able to produce any motion without assistance. Since we are able to accurately predict the intention of subjects that have not been involved in the training of the model, we expect this model will be able to calculate the intention of such patients. If this intention is used as input for a robotic rehabilitator, it is expected to perform a motion that describes more accurately the actual intention of the patient than a predefined trajectory, which is what is currently used in clinical setups.

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