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Convolutional Neural Network Approach for Elbow Torque Estimation during Quasi-dynamic and Dynamic Contractions

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***Abstract*— Accurate torque estimation during dynamic conditions is challenging, yet an important problem for many applications such as robotics, prosthesis control, and clinical diagnostics. Our objective is to accurately estimate the torque generated at the elbow during flexion and extension, under quasi-dynamic and dynamic conditions. High-density surface electromyogram (HD-EMG) signals, acquired from the long head and short head of biceps brachii, brachioradialis, and triceps brachii of five participants are used to estimate the torque generated at the elbow, using a convolutional neural network (CNN). We hypothesise that incorporating the mechanical information recorded by the biodex machine, i.e., position and velocity, can improve the model performance. To investigate the effects of the added data modalities on the model accuracy, models are constructed that combine EMG and position, as well as EMG with both position and velocity. R^2 values are improved by 2.35%, 37.50%, and 16.67%, when position and EMG are used as inputs to the CNN models, for isotonic, isokinetic, and dynamic cases, respectively compared to using only EMG. The model performances improves further by 2.29%, 12.12%, and 20.50% for isotonic, isokinetic, and dynamic conditions, when velocity is added with the EMG and position data.**

I. INTRODUCTION

The electromyogram (EMG) signal has been widely used for prosthesis control, medical rehabilitation, sports medicine, and clinical diagnostics [1]–[4]. The surface EMG, a non-invasive muscular activity detection method, has been used to estimate the level of generated muscle force by mapping a relationship between the electrical activity of the muscle (represented by the EMG amplitude) and the muscle force/ joint torque [5]–[8]. Muscle force/joint torque estimation is important in many applications such as controlling prosthetic hands and assistive devices [1], [9].

Different approaches have been used to estimate torque, based on EMG signals [5], [6], [10], [11]. Some studies have used Hill's muscle model [11] in which an appropriate estimation of muscle physiological parameters is needed. Other modeling methods, such as polynomial functions, artificial neural networks (ANNs), linear regression, and fast orthogonal search (FOS) are used to capture the EMG-force relationship, without requiring any knowledge about muscle and joint dynamics [5]–[8], [12], [13].

Using ANNs has shown promising results in EMG based force estimation [6], [7], [14]. Mobasser et al. investigated an ANN architecture for force estimation, under isometric, isotonic and light load (dynamic) conditions [7], where the model was able to predict the nonlinear relation between the EMG signal and the force generated at the wrist [7]. A relationship between EMG signal and the isokinetic elbow joint torque was determined using a 3-layer ANN, where the EMG signals obtained from the biceps and triceps, elbow joint angle, and velocity were used as inputs to the ANN and the results showed that the model estimated the joint torque reliably [14]. Hajian et al. used extracted time and frequency domain features from high density EMG (HD-EMG) signals, recorded from the elbow flexor muscles during isometric elbow flexion, to estimate force induced at the wrist using a multilayer perceptron neural network (MLPNN) [6]; they obtained a percent root mean square error (%RMSE) value of 6.21. A convolutional neural network (CNN) and long short-term memory (LSTM) network were used to estimate force from EMG signals [15], where the results suggested that the models were applicable for force estimation.

This study has two objectives. First, to estimate generated torque at the elbow from EMG under quasi-dynamic and dynamic conditions. Second, to improve the estimates by incorporating mechanical information into the model. Linear HD-surface electrode arrays with eight monopolar channels were used to record EMG signals obtained from the elbow flexor and extensor muscles, during isotonic, isokinetic (quasi-dynamic), and dynamic elbow flexion and extension. These EMG signals are then mapped to the generated torque at the elbow, using a CNN model. We improve the torque estimation performance by adding mechanical information namely position and velocity data to the model for the operational conditions.

II. METHOD

A. Data Collection

Five healthy subjects (3 females and 2 males; age 27 ± 6 years) were recruited for this study. The experimental procedures have been approved by the Health Sciences and Affiliated Teaching Hospitals Research Ethics Board (HSREB) of Queen's University, Kingston, Canada. Subjects provided informed consent before participating in the experiment. The experiments were conducted using the biodex model $840-000$, which is a reliable multi-joint system developed for testing and rehabilitation of the human musculoskeletal system. The biodex was set up for the elbow, as shown in Figure 1. Data were recorded as subjects performed isotonic, isokinetic (quasi-dynamic), and dynamic elbow flexion and extension. The isotonic case included 3 constant applied torque levels: 5, 8 and 12 Nm; and the isokinetic case included 3 constant rotational velocity levels: 60, 90 and 180

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deg/sec. There were no limitations on the applied torque level and velocity in the dynamic case. For each subject, the data were collected in one session with 12 trials per condition (2 sets of 6 repetitions with 30 seconds rest between sets). Torque, position and velocity data were recorded by the biodex. Appropriate rest periods were provided in order to avoid muscle fatigue.

The EMG signals were recorded using 4 linear HD-electrode arrays with 8 monopolar channels (5 mm spacing) from the long head and short head of biceps brachii, the brachioradialis, and the triceps brachii muscles. For the biceps muscles, the fourth electrode of each array was located at the SENIAM recommended sensor location. For the brachioradialis, the fourth electrode was placed at one-third the length of the forearm measured from the elbow. For the long head of triceps brachii, electrodes were placed at 50% of the distance between the posterior crista of the acromion and the olecranon at 2 finger widths medial to the line between them. The EMG data were collected using the Bioelecttronica EMG-USB2 high density (HD) system, which sampled the EMG data at 2048 Hz. A driven right leg (DRL) circuit was used to reduce the 60 Hz interference by attaching two reference electrodes on the right and left wrists. The experimental setup, showing a subject seated in the biodex machine, the EMG-USB2 HD-system and the HD-electrodes (with 8 monopolar channels) is shown in Figure 1.

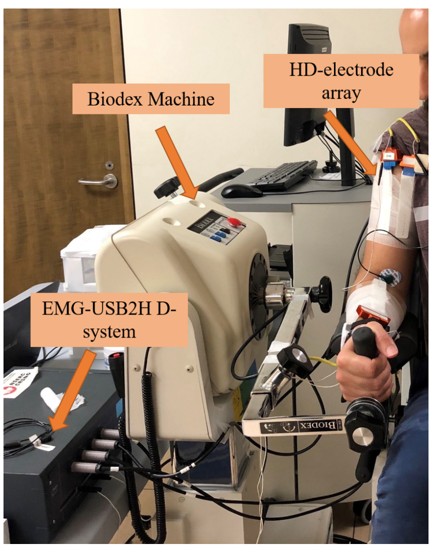

Fig. 1: The experimental setup, showing the biodex and HD-electrode arrays (8 sensors) mounted on the subject's arm, is presented.

B. Pre-processing

Differential HD-EMG signals are obtained by subtracting neighboring channels, resulting in 7 channels for each muscle. Each differential channel is band-pass filtered with cut-off frequencies of 10 Hz and 500 Hz using an eighth-order Butterworth filter to remove noise and artifact from EMG signals. Torque, position, and velocity signals recorded from Biodex, originally sampled at 1250 Hz, are up-sampled using linear interpolation to 2048 Hz, in order to match the sampling frequency of the EMG. The Biodex data are smoothed using a 300-point moving average filter. Then, the data during contraction are extracted and segmented for analysis, with segment length of 50 ms and overlap of half of the segment length. Then, the segmented EMG signals, position and velocity data are used as inputs to the model to estimate the torque generated at the elbow.

The differential EMG signals recorded from one channel of the elbow flexor and extensor muscles, the torque and position data recorded by the biodex, for an isotonic 12 Nm protocol from subject 3 are shown in Figure 2.

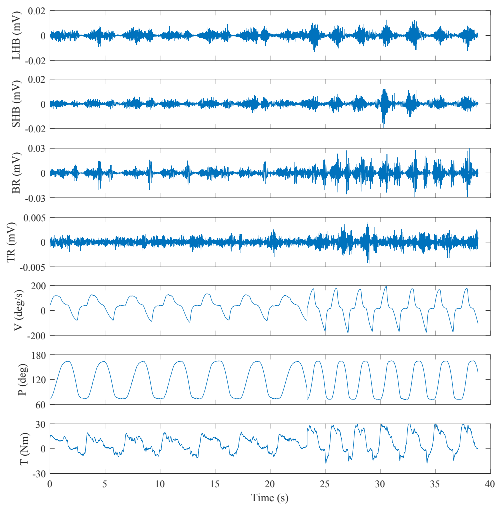

Fig. 2: Sample data recorded for 2 sets of contractions from one subject, during dynamic condition is shown. From top to bottom: EMG signals recorded from; LHB: long head of the biceps brachii, SHB: short head of the biceps brachii, BR: brachioradialis, and TR: triceps brachii; data recorded by the Biodex; V: velocity, P: position, and T: Torque.

C. Torque Estimation

Torque modelling is performed using a deep learning method, CNN, where the model's inputs are the raw EMG recordings of all channels of the four muscles. The ground truth outputs are the recorded torque measurements. An intra-subject training and validation scheme is used.

1) CNN Architecture: CNN is an extension of standard artificial neural networks, which is often used for image and video analysis, as well as other signals. CNN is capable of dealing with high-dimensional raw data, with no need for feature extraction, because it is able to learn from the data and extract features from it.

The CNN architecture has several layers, where the main components are convolutional and pooling layers. The convolutional layer computes the convolution of the input data by a set of filters; convolutions are executed by sliding the kernel (filter or feature detector) over the dimensions of the input data. Then, its output goes through a nonlinear activation function (such as a sigmoid, hyperbolic tangent, or rectified linear unit (ReLU)), where the non-linearity will be added to the model. A convolutional layer is usually followed by a pooling layer to reduce the dimensionality of the feature map, decrease computation, and avoid overfitting. A fully

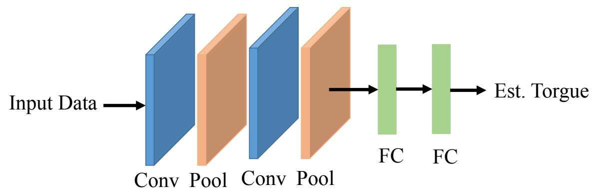

Fig. 3: The CNN architecture. Conv: convolutional layer, Pool: pooling layer, and FC: fully connected layer, where the last FC is the regression layer.

connected layer (dense layer), where each neuron receives input from all the neurons of the previous layer, can be used after several convolution and pooling layers. The final layer, which is also a fully connected layer with a single output neuron, is a regression layer which computes the output force.

The CNN model developed for this study consists of an input layer, two convolutional layers, where each layer has normalization and ReLU as an activation function, two maximum pooling layers (one after each convolutional layer), a fully connected (FC) layer, and a regression layer. The input layer takes segmented raw EMG data (28 differential signals), position, and velocity data. The convolutional layers have 16 and 64 filters, respectively, where all filters were 3×3. To avoid overfitting, L2 regularization is used. A batch size of 256 is used, since sizes below that result in longer training times while not improving the performance, and larger batch sizes decrease the regression accuracy. The number of training epochs is 100. Higher numbers do not improve the performance and result in longer training times, while fewer epochs reduce the performance. The first FC layer has 128 neurons. The CNN model's architecture is shown in Figure 3.

2) Model Training and Validation: The dataset is split into training and testing sets, where 5-fold cross-validation is used. The evaluation criterion used is R^2. Torque modeling is done in a subject-specific manner, so that the data for each subject are used separately to develop a model. The model is trained with the adaptive moment estimation (ADAM) algorithm as an optimizer, where the values used are, $\alpha = 0.001$, $\beta 1 = 0.9$, and $\beta 2 = 0.999$.

III. Results and Discussion

The elbow torque estimation is done for individual subjects, under the different quasi-dynamic and dynamic experimental conditions. The results are shown in Figure 4 for the test set, for the isotonic case with different torque levels, for the isokinetic case with different velocities, and for the dynamic case. We develop three CNN models to estimate the torque, where the model inputs are: i) the differential HD-EMG signals acquired from 4 muscles (28 channels); ii) the HD-EMG signals and position data (the elbow angle in degrees); and iii) the HD-EMG signals, position and velocity data. As shown in Figure 4, the average R^2 values across subjects improve by 2.47%, 1.17%, and 1.12% for isotonic cases (5, 8, and 12 Nm respectively) and by 26.78%, 36.95%, and 50% for isokinetic cases (60, 90, and 180 deg/sec respectively), and finally by 16.67% for dynamic case, when the position data are fused with the EMG data. When velocity information is also considered, the R^2 values improved for the isotonic conditions by 0%, 3.48%, and 2.22% for 5, 8, and 12 Nm respectively, and for the isokinetic conditions by 5.63%, 12.90%, and 20.63% for 60, 90, and 180 deg/sec respectively, compared to when EMG and position data are used. For dynamic condition, the performance improved by 20.50%, when the velocity data are incorporated in the model.

Accordingly, it can be observed that the incorporation of position and velocity data are more beneficial for the isokinetic and dynamic cases than the isotonic cases. Examining EMG signal amplitudes, it is apparent that for the constant torque (isotonic) contractions, the signal amplitude is approximately constant, despite the changing joint angle. For the isokinetic and dynamic conditions, the EMG amplitude and torque are not constant, and the EMG did not track the generated torque. Thus, it is possible to reliably estimate torque from EMG in the isotonic cases, but for the other two conditions, mechanical information is needed for acceptable torque estimation. Figures 5 and 6 show an example of estimated versus the measured torque for one subject during the isotonic 8 Nm, and dynamic conditions, where the obtained R^2 values are given.

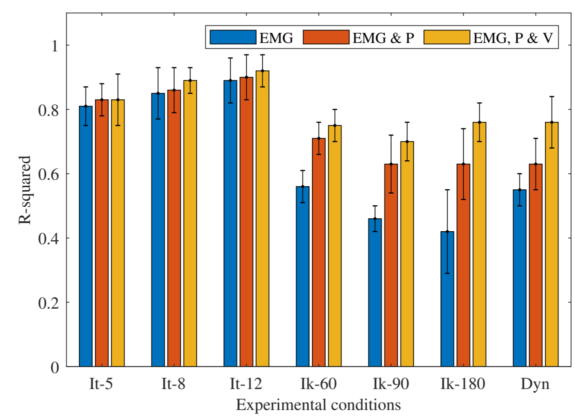

Fig. 4: The mean and standard deviation of R^2 values across the subjects for all three models using only EMG, EMG and position (EMG & P), and EMG, position and velocity (EMG, P & V) data for isotonic (It), isokinetic (Ik), and dynamic (Dyn) conditions.

We also compare our results obtained by the CNN model with MLPNN and support vector machine for regression (SVR) with linear, polynomial and radial basis function (RBF) kernels. For the MLPNN, we use two hidden layers of 16 and 20 dimensions, and the ReLU activation function. The batch size is 256, and the number of epochs is 100. The MLPNN is trained and tested with raw data and then the MLPNN and SVR are trained using a set of extracted features: mean absolute value, maximum and standard deviation of the EMG, position, and velocity signals, and the sum of the wavelength of the EMG signal. Our comparison results are shown in Table I as the average R^2 values across subjects for the models in which EMG, position, and velocity data are used. The CNN model's performance superior for all

TABLE I: COMPARISON OF R^2 VALUES BETWEEN DIFFERENT MODELS USING EMG, POSITION, AND VELOCITY INPUTS FOR ISOTONIC, ISOKINETIC, AND DYNAMIC CONDITIONS.

	Isotonic-5	Isotonic-8	Isotonic-12	Isokinetic 60	Isokinetic 90	Isokinetic 180	Dynamic
MLP (2 layers)	0.62 ± 0.21	0.56 ± 0.17	0.72 ± 0.18	0.12 ± 0.32	0.15 ± 0.34	0.26 ± 0.24	0.29 ± 0.11
MLP (features)	0.83 ± 0.09	0.80 ± 0.41	0.88 ± 0.07	0.15 ± 0.24	0.42 ± 0.11	0.35 ± 0.15	0.36 ± 0.18
SVM (RBF)	0.70 ± 0.16	0.70 ± 0.23	0.86 ± 0.08	-0.14 ± 1.12	0.50 ± 0.19	0.45 ± 0.21	0.36 ± 0.11
SVM (polynomial)	0.64 ± 0.17	0.21 ± 0.33	0.51 ± 0.21	-0.08 ± 1.22	0.37 ± 0.13	0.12 ± 0.25	0.22 ± 0.15
SVM (linear)	0.67 ± 0.06	0.64 ± 0.21	0.68 ± 0.12	-0.24 ± 1.21	0.25 ± 0.13	0.34 ± 0.26	0.14 ± 0.18
CNN	0.83 ± 0.08	0.89 ± 0.04	0.92 ± 0.05	0.75 ± 0.05	0.70 ± 0.06	0.76 ± 0.06	0.76 ± 0.08

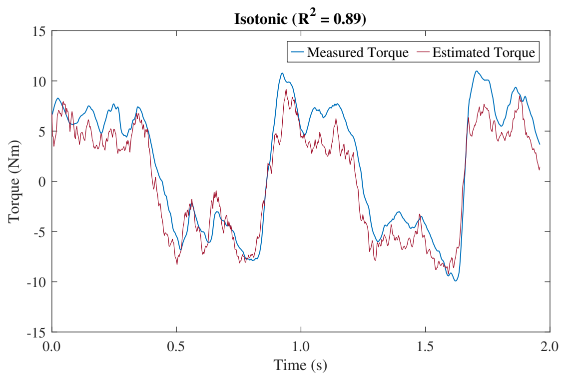

Fig. 5: The measured torque versus the estimated torque, for one subject, during isotonic (8 Nm) condition.

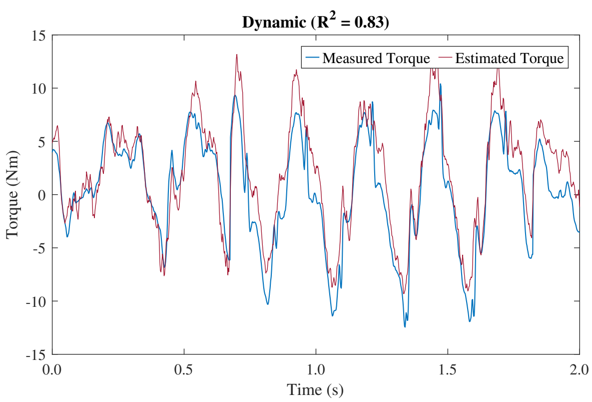

Fig. 6: The measured torque versus the estimated torque, for one subject, during dynamic contractions.

experimental conditions. The MLPNN models with features obtain close R^2 values to the CNN model for the isotonic cases. However, the CNN model does not need any feature extraction prior to the modelling, since the model itself is able to extract features. Also, the other methods are not able to estimate torque during isokinetic (especially 60 deg/sec) and dynamic contractions as well as the CNN.

IV. Conclusions and Future Work

Four HD-EMG electrode arrays were used to acquire EMG signals from the long head and short head of biceps brachii, brachioradialis, and triceps brachii during isotonic, isokinetic, and dynamic elbow flexion and extension. The purpose of this study was to estimate the generated torque at the elbow, using a CNN. We obtained average R^2 values of 0.85 ± 0.07, 0.48 ± 0.10, and 0.54 ± 0.05 for isotonic, isokinetic, and dynamic conditions using the EMG signals. Positional information is added to the model to investigate its effect on model accuracy. Our results show that the torque estimation improves when considering the mechanical information, especially for the isokinetic and dynamic cases. Thus, for fully dynamic contractions where the torque level, position, and movement speed are not controlled, the EMG signal will not be sufficient for reliable torque estimation, and incorporating mechanical information such as position and velocity is essential. For future work, to conduct a more comprehensive study, individuals across a wider age range and participants with neuromuscular problems may be considered.

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