Bidirectional joint torque prediction with EMG of multiple channels: both agonist and antagonist muscles are necessary

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Abstract: In numerous rehabilitation applications, joint motion is frequently required to be estimated through human muscle activity for motor control paradigm to impaired patients. Predicting joint torque in different degrees of freedom involves measurement of voluntary electromyography (EMG) on multiple muscle groups. From viewpoint of kinesiological discipline, agonist and antagonist muscle groups are respectively in charge of joint movement in different flexion/rotation directions. As a result, modeling and estimation of bidirectional joint motion follows to measure EMG signals of both agonist and antagonist muscles. Due to high possibility of drop off of EMG electrodes during motion, acquisition of some EMG channels may be missed and predicting joint torque with rest EMG channels occurs. This paper discusses the bidirectional joint torque prediction issue with complete and incomplete channels of EMG signals. The prediction results indicate that, EMG of both agonist and antagonist muscles are necessary to fulfill a promising bidirectional torque prediction, otherwise the prediction would be much degraded owing to lack of EMG on either agonist or antagonist muscle group.

Key Words: Torque prediction; electromyography (EMG); agonist and antagonist muscles

1 INTRODUCTION

Human movement is generated by various motion combinations of joints among human body. Rehabilitation techniques aim at restoring human motor function by driving their joint movement through assistive devices attached/equipped to impaired patients. In many rehabilitation applications, joint motion is usually estimated from biofeedback signals like electromyography (EMG) [1], and such biofeedback signals can be seen as reflection of human motion intention [2]. In order to accomplish joint movement control tasks by neuroprosthetics techniques, joint torque prediction is essential to be prior done to evaluate biomechanics modeling quality [3, 4, 5].

Base on kinesiology disciplines, agonist and antagonist muscle groups respectively can result in bidirectional joint movement [6]. Here, it is worthy explaining the meaning of "*agonist*" and "*antagonist*". *Agonist* muscles cause movement through their own contraction, while *antagonist* muscles oppose specific movement launched by *agonist* muscles [7, 8]. EMG is a technique to detect the muscle electrical activities and have been utilized in numerous rehabilitation scenarios such as controlling artificial prostheses and exoskeleton robots. As there exists evident correlation between volitional and evoked EMG and joint torque, EMG-torque modeling was established and many identifi-

cation/estimation approaches were proposed and developed [9, 5]. In Clancy *et al.*'s work [9], the joint torque can be predicted by the nonlinear models by considering multiple channels of EMG signals. This work utilized both EMG signals of agonist and antagonist muscle groups and achieved promising prediction performance on elbow joint. Further they involved joint angle information into the nonlinear model enhancing the prediction performance [10]. Li *et al.* introduced muscle synergy into reducing the dimension of multiple channels EMG signals so as to predict bidirectional joint torque [11]. Hughes and Chaffin extracted principle components of six channels of EMG to predict torso moment [12]. All of the aforementioned works considered EMG signals on both agonist and antagonist muscles to fulfill prediction of bidirectional joint torque in one degree of freedom.

During motor restoration tasks on multiple muscles, more surface EMG electrodes are demanded to be attached to the skins of subjects. It is high of possibility that some electrodes would drop off during intensive rehabilitation training and motor control [13, 14]. The drop-off of electrodes on some channels of EMG will make loss of acquisition on some channels of EMG, which may degrade the EMG-based motion estimation and control performances. Therefore, it is necessary to investigate how much such drop-off can affect the movement estimation tasks. This paper aims at assessing the impact how missing agonist or antagonist muscles' EMG signals would make influence on the bidi-

rectional joint torque predication in one degree of freedom. We will discuss the following two situations: 1) prediction based on only one agonist or only one antagonist muscle pair ; 2) prediction based on both agonist and antagonist muscle groups.

2 Experiment Setup and Data Processing

The EMG and the joint torque data were acquired from four able-bodied subjects (3 males and 1 female, 25∼31 years old, 59∼68 kg weight, and 164∼178 cm height at the time of the experiment). The subjects were seated on a chair with their right foot attached to a Biodex dynamometer (Biodex Medical Systems Inc., Shirley, NY, USA). The setting was 90 degrees for the ankle joint and 110 degrees for the knee joint while the joint center was aligned with the axis of the dynamometer. Straps were used on the pelvis and shoulders to secure subjects' position on the chair. Thigh movement was also restricted by a strap. The EMG electrodes were placed over the muscle belly of the SOL (Soleus), MG (Medial Gastrocnemius), and TA (Tibialis Anterior) muscles according to the "SENIAM" recommendation of electrodes placement based on crus anatomy [15]. The bipolar AgCl EMG electrodes (round with 2cm radius) were aligned along the direction of muscle fiber with 20mm interelectrode spacing. The reference electrode was placed on the patella of the contralateral leg. The subjects were informed to perform maximum voluntary contractions (MVC) in both plantar- and dorsi-flexion directions. They were then asked to voluntarily make the ankle plantar-flexion and dorsi-flexion movement randomly including both directional contractions and both fast-short and slow-long contractions. This random session which contains about 8-20 random contractions, was performed in isometric and in isotonic conditions. Synchronous acquisition of the joint torque and differential EMG signals were performed with a sample frequency of 2048Hz by the EMG100 amplifier (gain 1000) and the Biopac MP100 system (Biopac Systems, Inc., Santa Barbara, CA, USA). After acquisition, the raw EMG signals were rectified and then low-pass filtered with 10Hz cutoff frequency.

3 Joint Torque Identification and Prediction

3.1 Review of extreme learning machine (ELM)

In this paper, we utilize extreme learning machine (ELM) to identify and predict EMG-torque model. By making use of principles of ELM [16, 17], we attempt to describe the relationship between input and output of black-box model by using the feedforward neural network with single hidden layer. The output function of ELM is depicted as follows [16, 17].

$$f_L(\mathbf{x}) = \sum_{i=1}^{L} \beta_i h_i(\mathbf{x}) = \mathbf{h}(\mathbf{x})\beta$$

where $\beta = [\beta_1, \beta_2, \cdots, \beta_L]^T$ is the output weight between the hidden layer of L nodes and output nodes, and $\mathbf{h}(\mathbf{x}) = [h_1(\mathbf{x}), h_2(\mathbf{x}), \cdots, h_L(\mathbf{x})]^T$ are the nonlinear activation functions mapping the output of hidden layer from the input $\mathbf{x}$. In many engineering applications, nonlinear activa-

tion/mapping function is described by

$$h_i(\mathbf{x}) = G(\mathbf{a}_i, b_i, \mathbf{x})$$

where $G(\mathbf{a}_i, b_i, \mathbf{x})$ denotes nonlinear mapping function that can guarantee approximation capability of ELM, $\mathbf{a}_i$ is the input weight vector connecting the input layer to the ith hidden layer, b_i is the bias weight of the ith hidden layer. The commonly used nonlinear activation/mapping functions are as follows [16, 17].
Sigmoid function

$$G(\mathbf{a}_i, b_i, \mathbf{x}) = \frac{1}{1 + \exp(\mathbf{a}_i \mathbf{x} + b_i)}$$

Gaussian function

$$G(\mathbf{a}_i, b_i, \mathbf{x}) = \exp(b_i \|\mathbf{a}_i - \mathbf{x}\|)$$

Hard limit function

$$G(\mathbf{a}_i, b_i, \mathbf{x}) = \text{sgn}(\mathbf{a}_i \mathbf{x} + b_i)$$

Quadratic function

$$G(\mathbf{a}_i, b_i, \mathbf{x}) = (\|\mathbf{x} - \mathbf{a}_i\| + b_i)^{1/2}$$

ELM can be built with randomly initialized hidden nodes. Given a training set $\{(\mathbf{x}_i, \mathbf{y}_i) | \mathbf{x}_i \in R^M, \mathbf{y}_i \in R^M, i = 1, 2, \cdots, N\}$, where $\mathbf{x}_i$ is the training input vector, $\mathbf{y}_i$ represents the training output/target vector.
The general procedures of ELM training algorithm can be summarized as follows [16, 17].
Step 1. Randomly assign the hidden node parameters, e.g., the input weights $\mathbf{a}_i$ and biases b_i for additive hidden nodes, $i = 1, \cdots, L$.
Step 2. Construct the hidden layer output matrix

$$\mathbf{H} = \begin{bmatrix} \mathbf{h}(\mathbf{x}_1) \\ \mathbf{h}(\mathbf{x}_2) \\ \cdots \\ \mathbf{h}(\mathbf{x}_N) \end{bmatrix} = \begin{bmatrix} h_1(\mathbf{x}_1) & h_2(\mathbf{x}_1) & \cdots & h_L(\mathbf{x}_1) \\ h_1(\mathbf{x}_2) & h_2(\mathbf{x}_2) & \cdots & h_L(\mathbf{x}_2) \\ \vdots & \vdots & \ddots & \vdots \\ h_1(\mathbf{x}_N) & h_2(\mathbf{x}_N) & \cdots & h_L(\mathbf{x}_N) \end{bmatrix}$$

.
Step 3. Obtain the optimal output weight vector $\hat{\beta} = \mathbf{H}^\dagger \mathbf{Y}$, where $\mathbf{H}^\dagger$ is the Moore Penrose generalized inverse of matrix $\mathbf{H}$, target matrix is

$$\mathbf{Y} = [\mathbf{y}_1, \mathbf{y}_2, \cdots, \mathbf{y}_N]^T = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1M} \\ y_{21} & y_{22} & \cdots & y_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ y_{N1} & y_{N2} & \cdots & y_{NM} \end{bmatrix}$$

3.2 ELM for Torque Identification/Prediction with Voluntary EMG

Considering estimating/predicting the resultant torque in a range of containing flexion and extension directions with multiple muscles' EMG signals, the following nonlinear model describing the relation can be

$$\tau = f(\mathbf{u}_{agonist}, \mathbf{u}_{antagonist}) \qquad (1)$$

where τ is the joint toque, $\mathbf{u}_{agonist}$ and $\mathbf{u}_{antagonist}$ are respectively EMG signals of agonist and antagonist muscles, notation $f(\cdot)$ denotes the nonlinear mapping between EMG signals from multiple muscles and joint torque. Evidently, (1) is a black-box model should be identified with captured EMG and torque data. In order to describe and model the nonlinear mapping above, we present the relationship by utilizing the structure of the ELM with single hidden layer. In this work, we present the torque estimation/prediction structure based on ELM. For three muscles at the shank for eliciting ankle joint dorsi and plantar flexions, the aforementioned formulation on ELM can specifically become

$$
\tau = \begin{bmatrix} \tau(t_1) \\ \tau(t_2) \\ \vdots \\ \tau(t_n) \end{bmatrix}^T = f([\mathbf{u}_{SOL} \quad \mathbf{u}_{MG} \quad \mathbf{u}_{TA}]^T)
$$
$$
= \begin{bmatrix} f_{11}(u_{SOL}(t_1)) & f_{12}(u_{SOL}(t_2)) & f_{13}(u_{SOL}(t_n)) \\ f_{21}(u_{MG}(t_1)) & f_{22}(u_{MG}(t_2)) & f_{23}(u_{MG}(t_n)) \\ \vdots & \vdots & \vdots \\ f_{n1}(u_{TA}(t_1)) & f_{n2}(u_{TA}(t_2)) & f_{n3}(u_{TA}(t_n)) \end{bmatrix}
$$

where

$$
\mathbf{u}_{SOL} = [u_{SOL}(t_1), u_{SOL}(t_2), \cdots, u_{SOL}(t_n)]^T,
$$
$$
\mathbf{u}_{MG} = [u_{MG}(t_1), u_{MG}(t_2), \cdots, u_{MG}(t_n)]^T,
$$

and

$$
\mathbf{u}_{TA} = [u_{TA}(t_1), u_{TA}(t_2), \cdots, u_{TA}(t_n)]^T,
$$

respectively denote the EMG signals of SOL, MG and TA muscles from sampling instant t_1 to t_n.

For estimating joint torque with voluntary EMG signals of SOL, MG and TA muscles, the general formulation above becomes

$$
\mathbf{Y} := \tau = \begin{bmatrix} \tau(t_1) & \tau(t_2) & \cdots & \tau(t_n) \end{bmatrix}
$$

and

$$
\Phi := \mathbf{H} = \begin{bmatrix} h_1(\mathbf{u}_{SOL}) & h_2(\mathbf{u}_{SOL}) & \cdots & h_L(\mathbf{u}_{SOL}) \\ h_1(\mathbf{u}_{MG}) & h_2(\mathbf{u}_{MG}) & \cdots & h_L(\mathbf{u}_{MG}) \\ h_1(\mathbf{u}_{TA}) & h_2(\mathbf{u}_{TA}) & \cdots & h_L(\mathbf{u}_{TA}) \end{bmatrix}
$$

The estimated ankle joint torque $\tilde{\tau}$ would thus become

$$
\tilde{\tau} = \mathbf{H}\hat{\beta} = \Phi\beta
$$

where $\hat{\beta} = \mathbf{H}^\dagger \mathbf{Y} = \Phi^\dagger \tau$. Seen from the above procedures, we may see that the estimated ankle joint torque can be obtained from the measured torque and EMG of three muscles and the ELM is trained with $\hat{\beta}$ computed. We can also call it direct validation since the measured torque is involved to get the estimated one. Our goal of this paper is to predict the joint torque with multiple channels of EMG, and in the prediction phase which we can call cross validation, EMG signals are the only forth-coming information available as the input into the trained ELM to predict joint torque. In

the prediction phase starting from sampling instant t_{n+1}, we would have the newly-input EMG signals forming

$$
\Phi' = \begin{bmatrix} h_1(\mathbf{u}'_{SOL}) & h_2(\mathbf{u}'_{SOL}) & \cdots & h_L(\mathbf{u}'_{SOL}) \\ h_1(\mathbf{u}'_{MG}) & h_2(\mathbf{u}'_{MG}) & \cdots & h_L(\mathbf{u}'_{MG}) \\ h_1(\mathbf{u}'_{TA}) & h_2(\mathbf{u}'_{TA}) & \cdots & h_L(\mathbf{u}'_{TA}) \end{bmatrix}
$$

where

$$
\mathbf{u}'_{SOL} = [u_{SOL}(t_{n+1}), u_{SOL}(t_{n+2}), \cdots, u_{SOL}(t_{n+r})]^T,
$$
$$
\mathbf{u}'_{MG} = [u_{MG}(t_{n+1}), u_{MG}(t_{n+2}), \cdots, u_{MG}(t_{n+r})]^T,
$$

and

$$
\mathbf{u}'_{TA} = [u_{TA}(t_{n+1}), u_{TA}(t_{n+2}), \cdots, u_{TA}(t_{n+r})]^T,
$$

respectively denote the EMG signals of SOL, MG and TA muscles from sampling instant t_{n+1} to t_{n+r}. The predicted joint torque can thus be

$$
\hat{\tau} = \Phi'\beta
$$

Here we may find that the joint torque prediction utilizes the previously-identified EMG-torque relation based on ELM and newly-coming EMG signals. The difference between the identification and prediction phases may lie in that, in identification phase, the optimal weight $\hat{\beta}$ is obtained with both EMG and torque data; in prediction phase, only EMG is involved to form a new feature matrix $\mathbf{H}$ without computing again the optimal weight $\hat{\beta}$. In the ensuing parts, we will verify the efficiency of the ELM-based joint torque prediction method.

For non-isometric case, the above formulations would become by considering the force-length and force-velocity relation appeared in the classic Hill muscle model [18] as follows. In the identification phase, Φ would be changed as

$$
\Phi := \mathbf{H} = \begin{bmatrix} h_1(\mathbf{u}_{SOL}) & h_2(\mathbf{u}_{SOL}) & \cdots & h_L(\mathbf{u}_{SOL}) \\ h_1(\mathbf{u}_{MG}) & h_2(\mathbf{u}_{MG}) & \cdots & h_L(\mathbf{u}_{MG}) \\ h_1(\mathbf{u}_{TA}) & h_2(\mathbf{u}_{TA}) & \cdots & h_L(\mathbf{u}_{TA}) \\ h_1(\mathbf{pos}) & h_2(\mathbf{pos}) & \cdots & h_L(\mathbf{pos}) \end{bmatrix}
$$

where $\mathbf{pos} = [\mathrm{pos}(t_1), \mathrm{pos}(t_2), \cdots, \mathrm{pos}(t_n)]^T$ denotes the joint position information from sampling instant t_1 to t_n. In the prediction phase, the matrix Φ' becomes

$$
\Phi' = \begin{bmatrix} h_1(\mathbf{u}'_{SOL}) & h_2(\mathbf{u}'_{SOL}) & \cdots & h_L(\mathbf{u}'_{SOL}) \\ h_1(\mathbf{u}'_{MG}) & h_2(\mathbf{u}'_{MG}) & \cdots & h_L(\mathbf{u}'_{MG}) \\ h_1(\mathbf{u}'_{TA}) & h_2(\mathbf{u}'_{TA}) & \cdots & h_L(\mathbf{u}'_{TA}) \\ h_1(\mathbf{pos}') & h_2(\mathbf{pos}') & \cdots & h_L(\mathbf{pos}') \end{bmatrix}
$$

where $\mathbf{pos}' = [\mathrm{pos}(t_{n+1}), \mathrm{pos}(t_{n+2}), \cdots, \mathrm{pos}(t_{n+r})]^T$ denotes the joint position recordings from t_{n+1} to t_{n+r}.

4　Results

Based on the EMG and torque data of the four healthy subjects (Subjects 1∼4), we apply ELM with sigmoid function to investigate that the prediction performance involving agonist and/or antagonist muscles. The data sets of aforementioned joint torque and EMG signals are divided into two segments as identification and prediction phases

(a) Subject 1
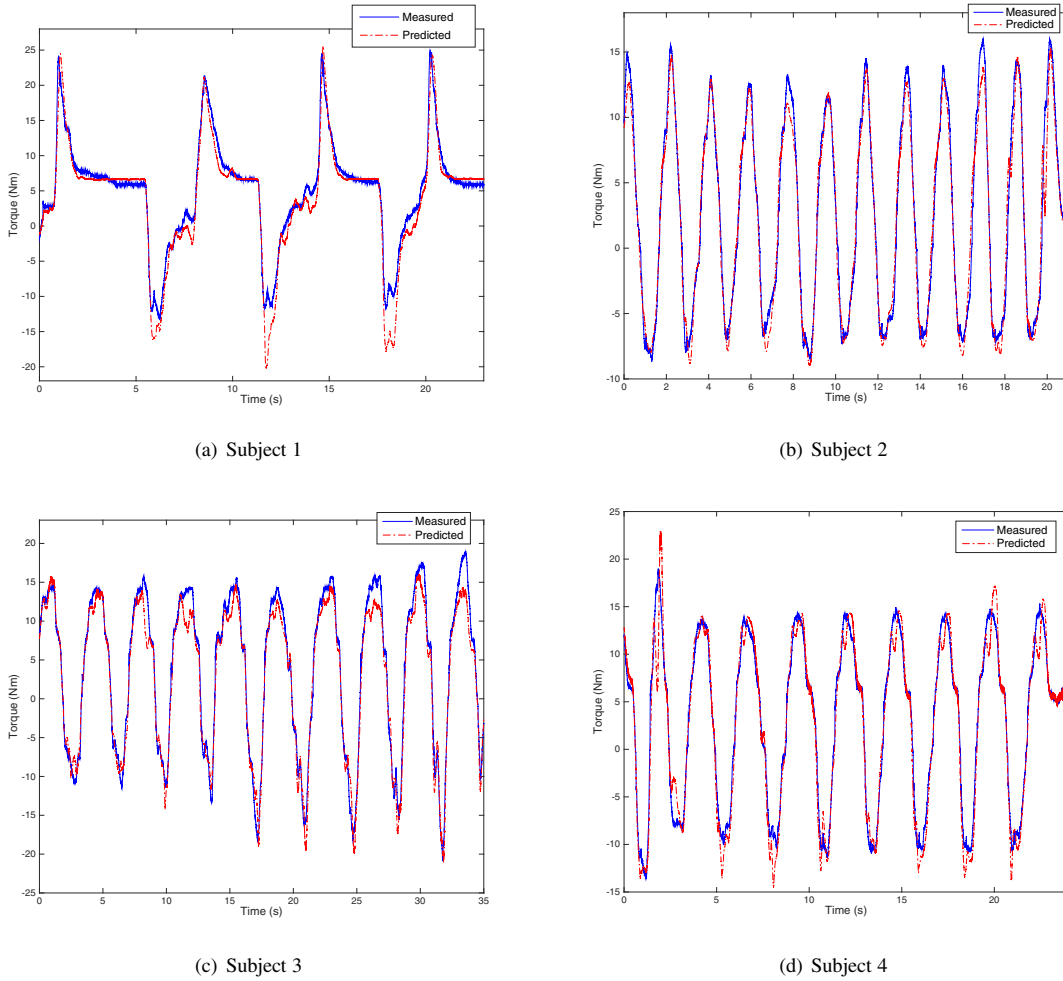
(b) Subject 2

(c) Subject 3

(d) Subject 4

Figure 1: Ankle joint torque prediction results of the four healthy subjects, with EMG signals of both agonist and antagonist muscles (SOL, MG, and TA muscles) as inputs involved into the ELM. Sigmoid function is adopted in the ELM with hidden nodes being $L = 20$.

with each one's sampling numbering ratios being approximately 1:1 respectively, in order to validate the efficiency of the proposed method based on ELM. The normalized root mean square error (NRMSE) and variance accounted for (VAF) are used as statistics indexes for evaluating the estimation/prediction performance of the proposed method and other methods for comparison. The NRMSE and VAF are defined as follows.

$$\text{NRMSE} = \sqrt{\frac{\|\tau - \hat{\tau}\|^2}{N}} \cdot \frac{1}{\max(\tau) - \min(\tau)}$$

and

$$\text{VAF} = 1 - \frac{var(\tau - \hat{\tau})}{var(\tau)}$$

where $\max(\cdot)$, $\min(\cdot)$, and $var(\cdot)$ denotes the maximum, minimum, and variance of vectors respectively. If VAF is closer to 1, the identification/prediction performance seems better. In this work, we validate the proposed torque prediction approach in isotonic condition. "Isotonic" means the joint is moving with position/velocity changed and constant (interaction) force load.

Fig. 1 shows the ankle joint torque prediction results of the four subjects in isotonic case, via ELM with EMG signals of SOL, MG and TA. From analysis of recent work [14], we know that, SOL and MG muscles are agonist muscles while TA muscle is antagonist muscle during plantar flexion of ankle joint, TA muscle is agonist muscle while SOL and MG muscles are antagonist muscles during dorsi flexion. EMG of both agonist and antagonist muscles (SOL, MG and TA) are used in ELM training and prediction. Seen from Fig. 1, we could see that the prediction results seem promising based on EMG of agonist and antagonist muscles.

As comparison, we try to predict the ankle joint torque with only one pair of agonist/antagonist muscles considered, i.e., the matrix Φ in the ELM formulation in isotonic case becomes

$$\Phi = \begin{bmatrix} h_1(\mathbf{u}_{SOL}) & h_2(\mathbf{u}_{SOL}) & \cdots & h_L(\mathbf{u}_{SOL}) \\ h_1(\mathbf{u}_{MG}) & h_2(\mathbf{u}_{MG}) & \cdots & h_L(\mathbf{u}_{MG}) \\ h_1(\mathbf{pos}) & h_2(\mathbf{pos}) & \cdots & h_L(\mathbf{pos}) \end{bmatrix}$$

(a) Subject 1

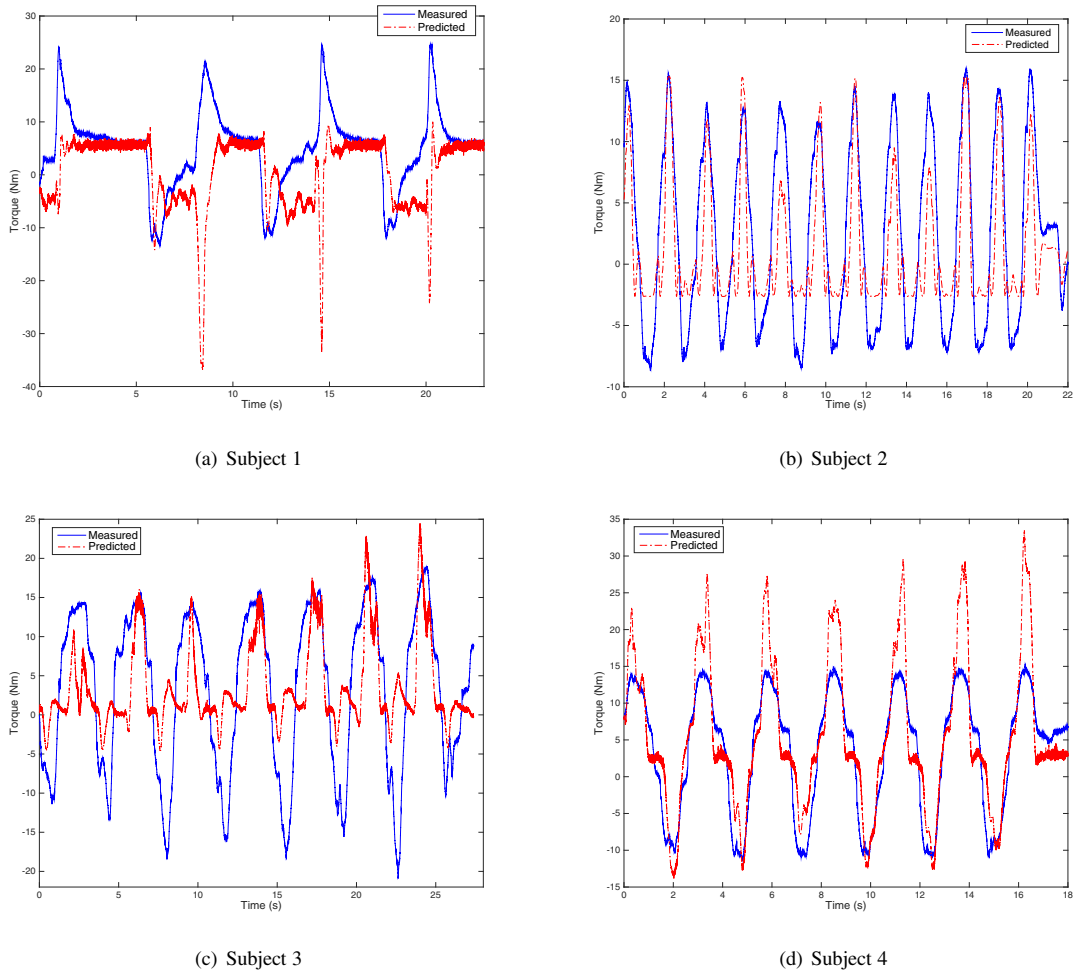(b) Subject 2

(c) Subject 3

(d) Subject 4

Figure 2: Ankle joint torque prediction results of the four healthy subjects, with only EMG signals of agonist muscle group (SOL and MG muscles) as inputs involved into the ELM. Sigmoid function is adopted in the ELM with hidden nodes being $L = 20$.

or/and

$$\Phi = \begin{bmatrix} h_1(\mathbf{u}_{TA}) & h_2(\mathbf{u}_{TA}) & \cdots & h_L(\mathbf{u}_{TA}) \\ h_1(\mathbf{pos}) & h_2(\mathbf{pos}) & \cdots & h_L(\mathbf{pos}) \end{bmatrix}$$

Such situation is realistic since the EMG electrodes on one side of muscle groups may drop off during motion. In this scenario, one may wonder whether joint torque prediction based on the residual acquisition of EMG works or not. Fig. 2 presents the ankle joint torque prediction based on EMG of only one side (TA muscle) of agonist/antagonist muscle groups in isotonic case, we can see that the prediction performances are much degraded as compared to those Fig. 1 shows. Tab. 1 shows the comparison of joint prediction based on whole or partial pair of agonist and antagonist muscles, we can see that the prediction results based on EMG of both agonist and antagonist muscles are better than those based on only one muscle group pair which is charge of dorsi/plantar flexion respectively. All of these demonstrate that EMG of both agonist and antagonist muscles are necessary for joint torque prediction.

5 Conclusion

This paper discusses the bidirectional joint torque prediction with complete and incomplete channels of EMG signals. The prediction results indicate that, EMG of both agonist and antagonist muscles are necessary to fulfill a bidirectional torque prediction, otherwise the prediction would be degraded with insufficient channels of EMG.

Acknowledgement

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Table 1: Prediction performance of ankle joint torque with multiple channels of EMG on the four healthy subjects. Comparisons are made on three situations of using EMG of different muscles: both agonist and antagonist muscles are used, only SOL and MG muscle are used, only TA muscle is used.

Subject No.	EMG of muscle group used	NRMSE (%)	VAF (%)
1	Both agonist and antagonist muscles	**5.26**	**95.23**
	Only SOL and MG muscles	14.20	50.65
	Only TA muscle	11.14	68.48
2	Both agonist and antagonist muscles	**4.76**	**97.48**
	Only SOL and MG muscles	19.58	59.49
	Only TA muscle	17.23	68.53
3	Both agonist and antagonist muscles	**4.74**	**97.79**
	Only SOL and MG muscles	20.61	37.38
	Only TA muscle	16.50	59.84
4	Both agonist and antagonist muscles	**3.84**	**98.50**
	Only SOL and MG muscles	20.79	58.50
	Only TA muscle	13.87	80.34
Overall average	Both agonist and antagonist muscles	**4.65±0.51**	**97.25±1.22**
	Only SOL and MG muscles	18.79±2.69	51.50±8.84
	Only TA muscle	14.68±2.39	69.29±7.29

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