Torque Prediction Based on Evoked EMG in Fatiguing Muscle Toward Advanced Drop Foot Correction

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Abstract

Electrical stimulation (ES) has been applied since 1961 for the correction of hemiplegic drop foot. One main drawback of the technique is the occurrence of early fatigue. Several studies attempted to propose solutions to decrease the fatigue, however no consensus was reached to date. This work aims to predict ankle torque using stimulus evoked EMG (eEMG) during different muscle fatigue states. Five healthy subjects participated in our study. Conventional stimulation for drop foot correction was applied by surface stimulation in sitting position. The results showed that no tendency between the changes in eEMG and torque with muscle fatigue was found among all subjects. However, the relationship variation in one subject gradually changed depending on muscle states. In this work, we carried out the torque prediction with an adapted parameters model according to muscle fatigue state by reidentification using the latest measurement. The prediction was improved with 21%~90.9% comparing to the fixed parameters model. The results revealed a promising approach to use evoked EMG for fatigue compensation in the application of drop foot correction.

Keywords: *drop foot correction, muscle fatigue, stimulus evoked EMG, electrical stimulation*

Introduction

Hemiplegic drop foot (DF) is a condition resulting from stroke where the subject cannot lift his or her foot or dorsiflex [1]. The lack of dorsiflexion results in a dragging of the leg and as a result has a significant impact on the person's gait [1]. Electrical stimulation (ES) is one of the existing solutions which are used to correct drop foot. Many researchers paid most attention to get optimal stimulation intensity profiles for the affected leg. An optimised stimulation envelope to reproduce the EMG pattern observed in the tibialis anterior (TA) during healthy gait was proposed in [1]. The changes in TA activity with walking speed was further considered to enable adaptive FES intensity envelope in [2]. A method providing with precise timing adaptation of the ES pattern to ensure a good coordination of the healthy and affected legs was proposed in [3]. In practice, the clinical implementation of ES for drop foot correction in hemiplegia is a challenging task. One of the challenges is the rapid onset of fatigue on the stimulated muscle. Thus, it is required to adjust stimulation parameters to provide optimal and tolerable treatment with minimal muscle fatigue. In previous researches, optimal stimulation patterns or modulation of stimulation parameters were proposed to reduce fatigue. However, no consensus was reached to date. Moreover, fatigue phenomenon is unavoidable with repetitive or prolonged stimulation and it usually occurs fast with ES on paralyzed muscles. Therefore, it is essential to predict force generation for precise ES closed loop control when the stimulated muscle becomes fatigued.

The aim of this work is to predict ankle torque preliminarily in healthy subjects for the application of ES induced ankle dorsiflexion. In our study, we propose to identify the eEMG-torque model adaptively to improve torque prediction.

Material and Methods

Experimental Setup

Five healthy subjects participated in this study. A commercial stimulator (Prostim) was used to induce sufficient dorsiflexion. The active (cathode) stimulating electrode was placed over the common peroneal nerve and the indifferent (anode) was placed over the TA muscle. The isometric ankle torque was measured by a calibrated dynamometer (Biodex), interfaced with an acquisition system (Biopac MP100). The subjects were seated on the chair with their right ankle at 90^o, while the foot was strapped on the pedal. Evoked EMG activity of TA was collected using bipolar surface electrodes. The electrodes were positioned on the TA muscle along muscle fiber direction with 20mm interelectrode spacing. The reference electrode was placed on the patella. The EMG signal was amplified (gain 1,000) and sampled at 4KHz.

Experimental Protocol

For each subject, the first step of the experiment is to find the optimal stimulation location, that is, inducing pure dorsiflexion but tolerable and painless. The second step is to find supramaximal stimulation amplitude. In order to imitate hemiplegic walking situation, sequences of 2s stimulation and 2s rest were applied during 30mn. Stimulation consists of a trapezoidal envelope with pulse width modulation. Each 2s stimulation train consists of 0.4s ramp-up, 1.2s plateau and 0.4s ramp-down. The maximum pulse width and stimulation frequency were fixed at 350 μs and 40Hz for all subjects.

Signal Processing

The stimulation artifacts were removed by means of blanking window to extract muscle response (Mwave) signal. The measured torque was offset with respect to the baseline of the torque measurement without stimulation. The torque data was lowpass filtered (6^{th} order, cutoff frequency 100Hz). The measured eEMG data was lowpass filtered (6^{th} order, cutoff frequency 300Hz). The eEMG data was divided into epochs with each epoch containing one Mwave. The mean absolute value (MAV) of eEMG was calculated every 9 Mwave through moving average. The mean torque during the same time window was simultaneously computed.

The measurements of torque and eEMG were used to identify the parameters of mathematical models for ankle torque prediction. A Hammerstein model was adopted to represent the contraction dynamics as proposed in [4]. The eEMG-torque model is shown as follows:

$$y(t) = \sum_{i=1}^{l} a_i[y(t-i)] + \sum_{j=1}^{m}\sum_{k=1}^{n} b_{jk}[x(t-j)]^k + c_0$$

Where *y(t)* is the torque output at time *t*, *x(t)* is the input, in this study, it is the MAV value of eEMG. The term c_o is used to fit any offset of the output torque. We choose *n=3* as in [4]. Different model order *(l,m)* was assumed to identify and validate the model. Finally we choose model order *l=3, m=4* to minimize the prediction error. A recursive least squares method was used to fit these parameters.

For model identification, past measured torque is used as the past torque *y(t-i)*. For torque prediction, past predicted torque is used as the past torque. In this case, model output $\hat{y}_p(t)$ based on the identified parameters can be computed as follows:

$$\begin{aligned}\widehat{y}_p(t) \;&=\; f[x(t-1), x(t-2), ...x(t-m),\\ &\quad \widehat{y}_p(t-1), \widehat{y}_p(t-2), ...\widehat{y}_p(t-l)]\end{aligned}$$

When force measurement is not available, this approach makes it possible to use evoked EMG as a synthetic force sensor. In this case, we initialized the predicted torque at zero when no stimulation was delivered to the muscle. Mean-squared prediction error (MSE) is used as prediction performance index.

Results

For each subject, in order to observe the global change tendency in torque and eEMG, the peak torque and peak MAV during every 2s stimulation train were calculated and then normalized against the maximum values during the whole stimulation duration. We did not find consistent relationship between the variation in eEMG and torque associated with muscle fatigue among these subjects. Fig. 1 showed the changes in torque and MAV of eEMG with fatigue in subject1. The initial 2mn stimulation resulted in significant potentiation of muscle activity, whereas the torque gradually decreased. From 1.4mn to 4.1mn, the torque maintained at the same level. However, the MAV underwent three different states: increase, transitional remain and finally decrease. We also found time-varying properties in the variation of eEMG and torque in all other subjects. This kind of dissociation due to muscle fatigue condition was also found in [5]. Therefore, it is difficult to obtain precise torque prediction using a fixed eEMG-torque model especially in prolonged stimulation.

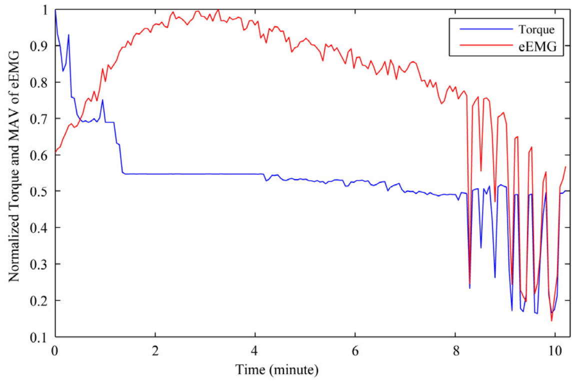

Fig. 1: The transition of the torque response and MAV of eEMG by stimulation in subject1. The results are normalized by the maximum values for the whole test.

In order to validate the model, we adopted two methods: 1) fixed parameters model as proposed in [4] and 2) our method based on adapted parameters model. For each subject, we divided the eEMG data into sets which contain 6 trains (33s). Then we subdivided every set into two epochs with each epoch containing 3 trains (16.5s). In the first approach, we applied the initial 16.5s data in first set to identify model and fixed the model parameters to predict all the following ankle torque. In the second approach, we applied the data during the first epoch (16.5s) in each set to identify model. Then the obtained parameters were used to predict the torque just during the adjacent epoch (16.5s) in the same set. The process was repeated for every set during the whole stimulation duration. Summary of the prediction performance is shown in TABLE I. Test1~Test4 were selected at different time instances to have different muscle states in terms of muscle fatigue. We can find that the prediction is less precise or difficult with the fixed model (e.g. test2, test3 in subject1) during long-term repetitive stimulation. However, when the model was reidentified with the latest data as our approach did, the prediction errors were greatly reduced as shown in TABLE I.

TABLE I

SUMMARY OF THE PREDICTION ERROR OBTAINED WITH FIXED OR ADAPTED eEMG- TORQUE MODEL

Subject	Model	Mean Square Error			
		Test1	Test2	Test3	Test4
S1	Fixed	0.0317	0.175	0.14	0.0876
	Adapted	/	0.0158	0.0138	0.0218
S2	Fixed	0.0354	0.0359	0.039	0.0567
	Adapted	/	0.0227	0.0223	0.00872
S3	Fixed	0.0505	0.0473	0.0448	0.0651
	Adapted	/	0.0373	0.0206	0.0342
S4	Fixed	0.0586	0.0854	0.0846	0.0734
	Adapted	/	0.0592	0.0328	0.0402
S5	Fixed	0.0256	0.0512	0.156	0.104
	Adapted	/	0.0178	0.0256	0.0476

In figure 2, we selected three sets of data (Test1, Test2 and Test 4) at three different muscle fatigue states in subject2 to compare the prediction performance of both approaches. MSE1 and MSE2 respectively indicate the prediction error with fixed and adapted model. 30mn stimulation resulted in torque loss from (a) 100%, to (b) 60%, until (c) 20% mainly due to muscle fatigue. The prediction with fixed model became less precise over time. Nevertheless, the torque prediction was greatly improved with adapted model.

Discussion and Conclusions

Our study focuses on the prediction of ankle torque based on evoked EMG in the context of ES drop foot correction during different muscle fatigue states. 5 healthy subjects participated in the experiments. During 30mn stimulation applied in isometric conditions, the torque declined in all subjects. The change of eEMG did not represent tendency among them. However, eEMG-torque relationship was gradually varied according to muscle fatigue condition in the same subject. Despite this kind of dissociation between eEMG and torque, we were able to apply our adapted eEMG-torque model to highly improve prediction performance comparing to fixed model which was commonly used in previous researches. Thereby, the effect of adapted identification should be significant and this approach has great potential for contribution of ES closed loop control with fatigue consideration. The future work includes to validate the results in hemiplegic subjects, to extend the present method to on-line automatic identification and adaptive control of ES for fatigue compensation towards advanced drop foot correction.

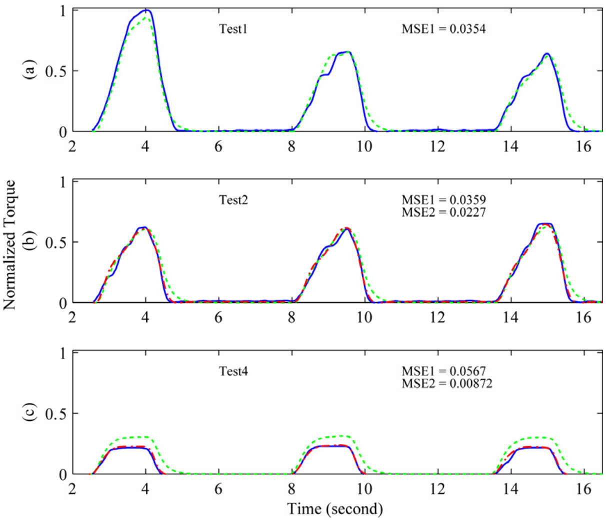

Fig. 2: The measured torque and predicted torque based on evoked EMG in different muscle fatigue state in subject2. The measured torque (blue), the predicted torque with fixed model (green dotted) and the predicted torque with adapted model (red dashdotted) are shown.

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