Preprints of the 21st IFAC World Congress (Virtual)
Berlin, Germany, July 12-17, 2020

Estimating Elbow Torque from Electrical Stimulation using a Particle Filter

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Abstract:
This study analyses the relationship between functional electrical stimulation (FES) and the induced torque for elbow flexion. The aim is to develop an FES-torque model that is simple to implement and understand, and is easily invertible so that the required FES for a desired assistive torque can be determined to enable control by FES. For accurate control, the FES-torque model must also be adaptable to time-varying behaviour of the muscle such as fatigue. The proposed FES-torque model is a sigmoid function, and a particle filter is implemented to estimate the change in parameters of the sigmoid function over time. The results show that the particle filter is successfully able to adapt to changes in the FES-induced torque and can be used to improve the estimate of FES-induced torque, with an overall average RMS error of 0.24 N.m or 7.85%. The improved FES-torque estimate allows for simple and more effective control of FES assistance and better fatigue management.

Keywords: Functional Electrical Stimulation (FES), FES-induced torque, Rehabilitation, Fatigue, Muscle response, Particle filter, Hybrid Exoskeleton, Assist-as-need

1. INTRODUCTION

Stroke is one of the leading causes of disability worldwide. Patients are able to regain strength and functionality by doing frequent exercise, however, it may not be possible to always have a physiotherapist to guide a patient through the exercises. Recovery from stroke can be improved using exoskeletons to assist with limb movement, as exoskeletons can automate the movement and increase exercise frequency. Further improvements for recovery can be obtained by augmenting exoskeletons with functional electrical stimulation (FES). FES is the application of electrical current to a muscle to elicit a contraction. As the stimulation directly activates the muscle, FES is an effective method to develop muscle strength and sensory awareness. The biggest disadvantage is that FES can cause fatigue. However, this fatigue can be compensated using a motor-driven exoskeleton. With accurate control of FES, an exoskeleton can balance the assistance provided by electric motors and FES to provide the benefits of both methods, suit the patient's needs, and manage fatigue.

However, FES can be difficult to control precisely as the muscle response is non-linear and time-varying. There have been simple methods to model and control FES. Rong et al. (2012) set the FES as a linear function of the measured electromyography (EMG), and Rouhani et al. (2017) used a first order transfer function to estimate torque from the FES amplitude. Other methods include adaptability to the time-varying behaviour, such as iterative learning control (Xu et al., 2014)(del Ama et al., 2014)(Ha et al., 2016), a Kalman filter with a forgetting factor (Zhang et al., 2011)(Qin Zhang et al., 2013), and a NARX-RNN approximator (Li et al., 2012). In Li et al. (2016) the Kalman filter and NARX-RNN approximator are compared. Both methods aim to predict the FES-induced torque without a sensor. However, there is still some error, and the error can increase over time, requiring recalibration with the sensor.

An issue for many of the control methods is fatigue management. In previous studies it is common to see that as FES-induced fatigue occurs, and the resulting torque decreases, the stimulation intensity is increased to maintain the desired torque. Increasing the stimulation intensity can cause more fatigue, which will shorten therapy time and may cause pain for the subject. It is more useful to estimate the FES-induced torque while accounting for changes in muscle behaviour due to fatigue, and to use this to reduce the stimulation intensity for better fatigue management and extended therapy time.

The aim of this study is to develop a simple FES-torque model that it is easy to use, easy to derive, and can be invertible, while being able to account for variability in the FES response. This study is part of a larger project to develop a hybrid exoskeleton that combines an electric motor with FES. An accurate FES-torque model allows for independent control and accurate balancing of FES and motor assistance to suit a patient's needs. A hybrid exoskeleton employing FES and an external actuator would also allow for better fatigue management, as the FES assistance can be reduced and actuator assistance increased to allow the patient to recover and extend the therapy time. The reason for implementing torque control, as explained in Chatfield

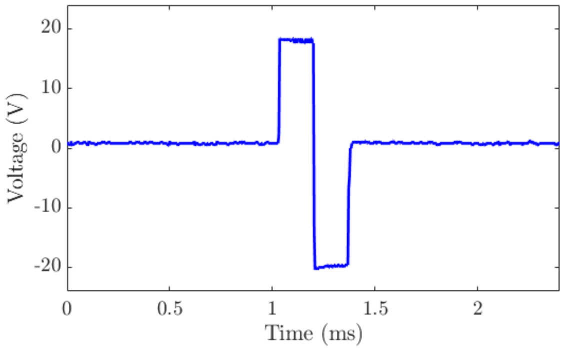

Fig. 1. A single stimulation wave, with a pulse width of approximately 135 microseconds.

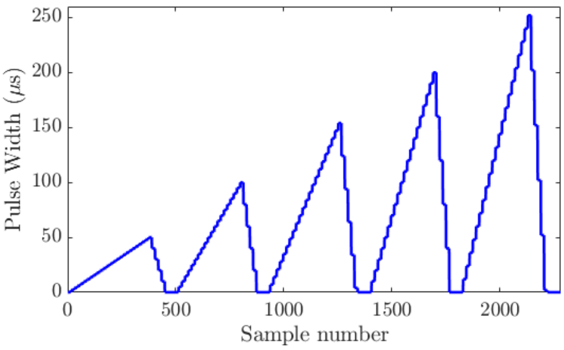

Fig. 2. The stimulation pattern applied during one cycle. There is a 10 second rest between each stimulation.

et al. (2019), is so that the assistance provided to a person is directly based on their strength and capabilities for assist-as-need control. In addition, an FES-torque model will make it easier to balance FES and motor effort.

To achieve this FES-torque model a logistic function (sigmoid curve) is proposed, and a particle filter similar to that in Chatfield et al. (2018) and implemented in Chatfield et al. (2019) is used to account for the variability in the muscle response to FES. Section 2 describes the methodology of the testing, Section 3 describes the selection of the FES-torque model, Section 4 details the implementation of the particle filter, followed by results in Section 5, discussion in Section 6, and the conclusion in Section 7.

2. METHODOLOGY

The exoskeleton developed and described in Chatfield et al. (2018) and Chatfield et al. (2019) is used for this study, with the motor kept stationary. A series elastic actuator (SEA) is formed by adding an elastic polyurethane part to the motor shaft for compliance. During the experiment, the subject wears the exoskeleton and FES is applied on the biceps brachii of the subject, resulting in dynamic elbow flexion. The stimulation pulse width, relative displacement across the SEA, and the elbow angle are recorded to determine the torque exerted across the SEA, the torque about the elbow due to gravity, and inertial torque, caused by the FES. The commanded stimulation intensity is sent from an STM32F4 microcontroller at 100 Hz. The raw angular measurements are sampled at 1 kHz and averaged at 100 Hz. The data recorded is analysed offline, which involves model calibration (Section 3) and applying the particle filter to estimate FES-induced torque (Section 4).

The circuit described in McKenzie et al. (2018) is used to deliver the stimulation through surface electrodes placed over the biceps brachii. The electrodes are 40 mm by 40 mm Verity Medical electrodes (model number VS4040). The biphasic FES waveform produced by the hardware is shown in Fig. 1. For this study, the amplitude is fixed at approximately 6 mA, the pulses occur at 50 Hz, and the pulse width is varied.

The commanded pulse width cycle is shown in Fig. 2. As can be seen the pulse width gradually increases. When increasing the stimulation, the pulse width increments in twenty steps, whereas when decreasing the stimulation, the pulse width decrements in five steps. The pulse width increments (decrements) every 150 milliseconds, so a stimulation period is approximately 3 seconds. The pulse width for each stimulation is gradually incremented to make the stimulation more comfortable for the subject, rather than to apply a sudden high stimulation intensity from rest. The set pulse width limit for a stimulation depends on how far through the cycle the subject is. What is not shown in Fig. 2 is that after a completed stimulation (when the pulse width is reset to zero) there is a rest time of 10 seconds before the FES is applied again. At the end of the cycle there is a 20 second rest period, and then the next cycle with the same stimulation pattern as in Fig. 2 is applied.

The subjects are three healthy males. This study was approved by the University of Canterbury Human Ethics Committee (HEC 2019/26).

3. MODEL DEVELOPMENT

The aim for the FES-torque model is that it must be parsimonious and easily invertible. During initial testing (not shown) it was observed that the FES-torque relationship was similar to a sigmoid, or the logistic function. A similar trend can be seen in Kirsch et al. (2017) when increasing the stimulation current. The logistic function also follows behaviour described in Kirsch et al. (2017) with minimal change in the produced torque as the stimulation intensity increases after a certain point. Additionally, Rouhani et al. (2017) use a transfer function that depends on an exponential term, similar to the logistic function. The logistic function proposed for this work is

$$\tau_F = \frac{a}{1 + e^{-b(\mathrm{PW}-d)}} + c, \tag{1}$$

with τ_F being the FES-induced torque (N.m), PW is the pulse width delivered (μs), d is the pulse width at which the midpoint of the logistic function occurs (μs), a is the maximum torque with zero offset (N.m), b describes the gradient of the curve, and c is the torque offset (N.m). Knowing the parameters, (1) can be rearranged as

$$\mathrm{PW} = \frac{-\ln(\frac{a}{\tau_{\mathrm{des}}-c} - 1)}{b} + d \tag{2}$$

to obtain the pulse width for a desired torque (τ_{des}). A calibration stage is performed by taking a single pulse width cycle and the FES-induced torque during that cycle, and determining the parameters of (1) that fit the cycle data. The estimated parameters are the basis of the initial hypotheses of the particle filter.

4. PARTICLE FILTER

The model developed in (1) does not account for the time-variability of FES-induced torque, and there can still be error and variability in the estimated torque. A particle filter is proposed to improve the estimate of FES-induced torque. A particle filter is a non-parametric Bayes filter that considers a motion model, a sensor model, and their variances to improve the estimate of the system's states (Thrun et al., 2002). The particle filter can be used for non-linear and time-varying systems. A particle filter was previously developed in Chatfield et al. (2018) and implemented in Chatfield et al. (2019) to improve the estimate of voluntary torque exerted by a subject during elbow flexion. In this study a different approach is taken as the particle filter finds the parameters in (1) that provide the best estimate of the FES-induced torque.

The particle filter generates of number of hypotheses (particles). In this study there are $N = 50$ particles. Particle m at time t is described as

$$\boldsymbol{x_t}^{[m]} = \left[a_t^{[m]} \ b_t^{[m]} \ c_t^{[m]} \ d_t^{[m]} \right]^T, \tag{3}$$

a vector with four states that represent a hypothesis of the FES-torque model parameters. The initial particle states are spread around the parameters found in the model calibration stage in Section 3. The motion model is

$$\boldsymbol{x_t}^{[m]} = \boldsymbol{x_{t-1}}^{[m]} + \begin{bmatrix} \mathcal{N}(0, 0.01) \\ \mathcal{N}(0, 0.00001) \\ \mathcal{N}(0, 0.01) \\ \mathcal{N}(0, 0.01) \end{bmatrix}. \tag{4}$$

The motion model updates each particle by adding process noise to each state, which in this study is considered as normally distributed noise $\mathcal{N}(\mu, \sigma)$ with a mean of μ and standard deviation σ. The standard deviation for each particle state was experimentally determined, and the mean was set as zero. It was noticed that when (1) is calibrated at different times during the exercise, the value for b changes within approximately 10%, hence why it is given a much smaller process noise than the other particle states. The FES-induced torque for each particle ($h_t^{[m]}$) is estimated by

$$h_t^{[m]} = \alpha(h_{t-1}^{[m]} + \mathcal{N}(0, \sigma_h)) + (1 - \alpha)\tau_{F,t}^{[m]}, \tag{5}$$

a weighted sum of the previous torque estimate ($h_{t-1}^{[m]}$) for the particle and the estimate ($\tau_{F,t}^{[m]}$) calculated when substituting the particle's states into the logistic function (1). To account for error between the current and previous torque estimate, normally distributed noise is added to the previous estimate. In this study $\sigma_h = 0.2$ and $\alpha = 0.5$.

The particle filter ranks each particle using a sensor model.The sensor measurement z is the same as in Chatfield et al. (2018) as

$$z = \tau_g - \tau_a, \tag{6}$$

representing the difference between the torque about the elbow due to gravity (τ_g) and the torque across the series elastic actuator (τ_a). The weight of a particle ($w_t^{[m]}$) is calculated by

$$w_t^{[m]} = w_{t-1}^{[m]} f_v(z_t - h_t^{[m]}), \tag{7}$$

where the particle's previous weighting ($w_{t-1}^{[m]}$) is multiplied by the sensor's probability density function f_v, which compares the estimated torque for the particle calculated by (5) to the sensor measurement. The probability density function for the sensor noise is described by

$$f_v(u) = \frac{\lambda}{\sigma_v \sqrt{2\pi}} e^{-(\lambda|u| + \frac{u^2}{2\sigma_v^2})}, \tag{8}$$

with $\lambda = 0.5$ and $\sigma_v = 0.2$. The probability density function represents a combined Gaussian distribution and exponential distribution. In this study the motor is stationary and inertia has minimal impact on the overall torque, so the sensor model is a reasonable estimate of the total torque. To account for the error and variance the sensor model will have when the motor is moving, and when the subject is voluntarily moving their arm, the sensor model has a wider distribution compared to a Gaussian distribution.

Finally, the FES-induced torque estimated by the particle filter ($\tau_{\mathrm{PF},t}$) is calculated by

$$\tau_{\mathrm{PF},t} = \frac{\sum_{n=1}^{N} w_t^{[n]} h_t^{[n]}}{\sum_{n=1}^{N} w_t^{[n]}} \tag{9}$$

and the best model parameters ($\boldsymbol{x_t}^{[\mathrm{PF}]}$) are estimated by

$$\boldsymbol{x_t}^{[\mathrm{PF}]} = \frac{\sum_{n=1}^{N} w_t^{[n]} \boldsymbol{x_t}^{[n]}}{\sum_{n=1}^{N} w_t^{[n]}}. \tag{10}$$

When the particles are resampled (using sequential importance resampling) they are generated closer to $\boldsymbol{x_t}^{[\mathrm{PF}]}$ and their weights are reset to one. The estimated parameters in $\boldsymbol{x_t}^{[\mathrm{PF}]}$ can change rapidly and appear noisy, so to provide a smoother transition in parameters for easier control the moving average ($\boldsymbol{x_t}^{[\mathrm{avg}]}$) of $\boldsymbol{x_t}^{[\mathrm{PF}]}$ is taken over the previous $L = 1000$ estimates, shown as

$$\boldsymbol{x_t}^{[\mathrm{avg}]} = \frac{\sum_{i=0}^{L-1} \boldsymbol{x_{t-i}}^{[\mathrm{PF}]}}{L}. \tag{11}$$

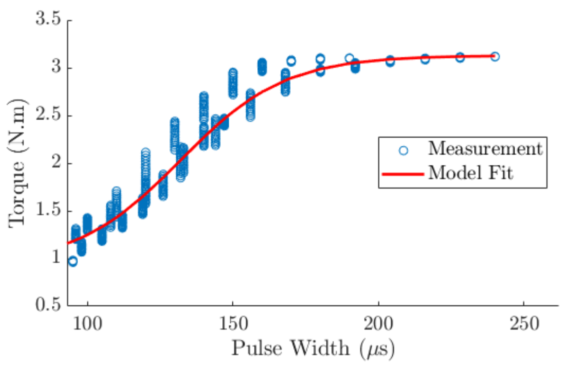

Fig. 3. FES-induced torque from the biceps for Subject 2, Spearman correlation $R = 0.98$.

Table 1. Average RMS error between the FES-torque model (1) and measured torque.

	Subject / Trial				Average
	1/1	1/2	2/1	3/1	
RMSE (N.m)	0.22	0.12	0.23	0.38	0.24
RMSE (%)	7.69	6.42	7.12	10.19	7.85

The parameters in $\boldsymbol{x}_t^{[\text{avg}]}$ are then used to estimate the FES-induced torque according to (1).

5. RESULTS

Figure 3 shows how well the logistic function described in (1) fits to FES-torque data captured during the model calibration stage for Subject 2. The logistic function provides a reasonable fit, however, it can be observed in Fig. 3 that there is variance in the FES-torque relationship.

Figure 4, Fig. 5, and Fig. 6 show trials for the three subjects with the measured torque, the particle filter estimate of the FES-induced torque, and the FES-induced torque estimated by the model (1) and the parameters from (11). Fatigue can be observed when the FES-induced torque decreases over time, and the particle filter and FES-torque model are able to adapt to the change in muscle response, improving the estimate of FES-induced torque. The adaptability can also be observed in Fig. 7, which shows the FES-torque model parameters, $\boldsymbol{x}_t^{[\text{avg}]}$, over time.

The RMS errors for the entire exercise for four trials are shown in table 1. A Monte Carlo approach was taken by applying the particle filter over 1000 times to each trial data set to calculate the average error. The RMS error is the difference between the measured torque and the FES-torque model, and the RMS error is also shown as a percentage of the maximum measured torque to compare to other research. The average RMS error across the trials was found to be 0.24 N.m or 7.85%.

6. DISCUSSION

The results show that the particle filter can adapt to the time-variable behaviour of the muscle response to FES, and can be used to determine changes in the FES-torque model parameters over time to improve the estimate of FES-induced torque. The improved FES-induced torque estimate allows for more accurate control of the stimulation for a desired assistive torque and better fatigue management. The average RMS error for all trials was found to be 7.85%, which is comparable to recent studies such as Li et al. (2016). However, previous studies mostly focus on lower-limb muscles that can produce larger torques or they focus on isometric contractions. As this study considered dynamic elbow flexion, the particle filter may need to be tested on lower-limb muscles and for isometric contractions for a direct comparison to previous studies.

A moving average of the parameters was used to make the control of FES for a desired torque easier for later research. The particle filter could cause a rapid change in the estimate of a model parameter, which if significant enough could cause a sudden change in the stimulation provided. This was also considered when selecting the process noise added to the particles while still allowing the particle filter to be adaptable to changes in torque. Taking the moving average slows the rate of change of the parameters, which provides a more stable stimulation for a desired assistive torque. The particle filter is robust to noise added to the sensor model, and using a moving average of the parameters further increases the robustness of the FES-torque model to noise. Further work could modify the length of the moving average or the process noise in (4) to depend on the rate of fatigue, which could be estimated by analysing the change in model parameters or torque. If the subject fatigues rapidly, then the process noise can be increased for the particle filter to converge to the change in torque faster, or the length of the moving average can be reduced to allow the model parameters to change faster.

With the improved FES-torque model, the assistance provided by FES and an electric motor on a hybrid exoskeleton can be more accurately balanced. If a patient is fatiguing, then the FES can be reduced and motor assistance increased to achieve the same total assistive torque for the movement, allowing the patient to recover and extend the therapy time. There is still error in the FES-torque prediction, which could result in too much or too little total assistance provided to a person. A possible solution is to incorporate the error in the FES-torque prediction into the motor control. The error can be approximated as the difference between the FES-torque model and the particle filter torque estimate, since the particle filter will be closer to the true torque. The ratio of motor to FES assistance would change slightly from what was initially set, but this would not be a significant change. The combined motor and FES assistance would be equal to the torque the person needs to complete the movement, achieving assist-as-need control. Another consideration is that the rate of change of motor assistance can also depend on the fatigue rate of the FES-induced torque.

The particle filter is useful to account for fatigue and will be important for balancing motor and FES assistance. However, fatigue management could possibly be improved if the onset of fatigue can be detected earlier. It is suggested in De Luca (1984) that a change in amplitude and frequency spectrum of EMG may indicate the onset of fatigue. This requires more research to verify, but it could be another method to reduce FES effort and increase motor assistance earlier to reduce or delay fatigue.

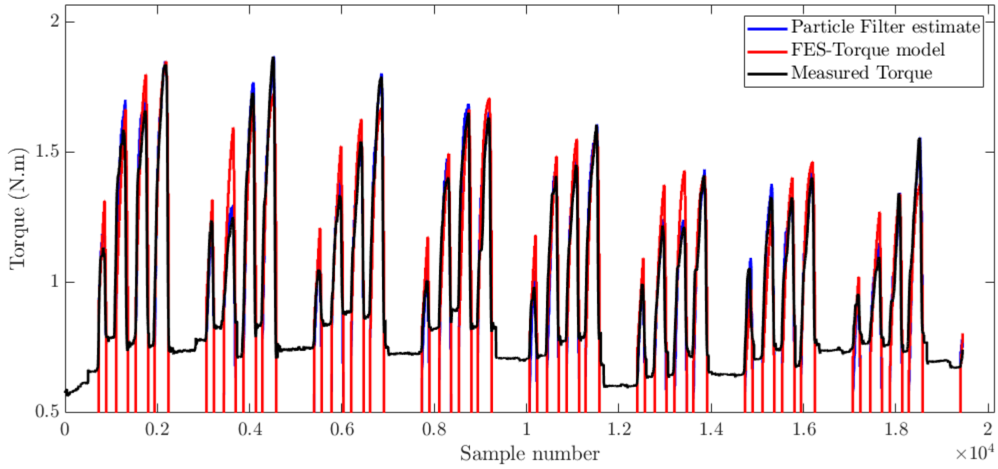

Fig. 4. FES-Torque estimation for Subject 1, Trial 2.

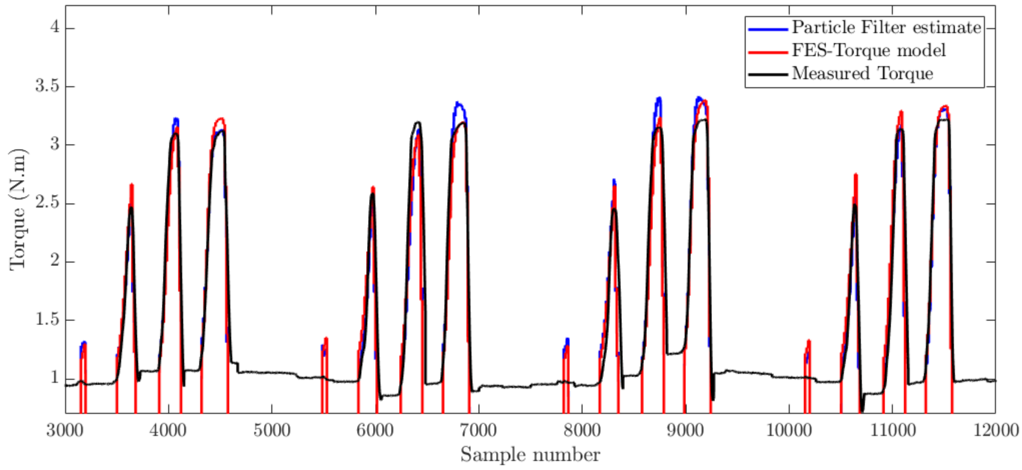

Fig. 5. FES-Torque estimation for Subject 2, Trial 1.

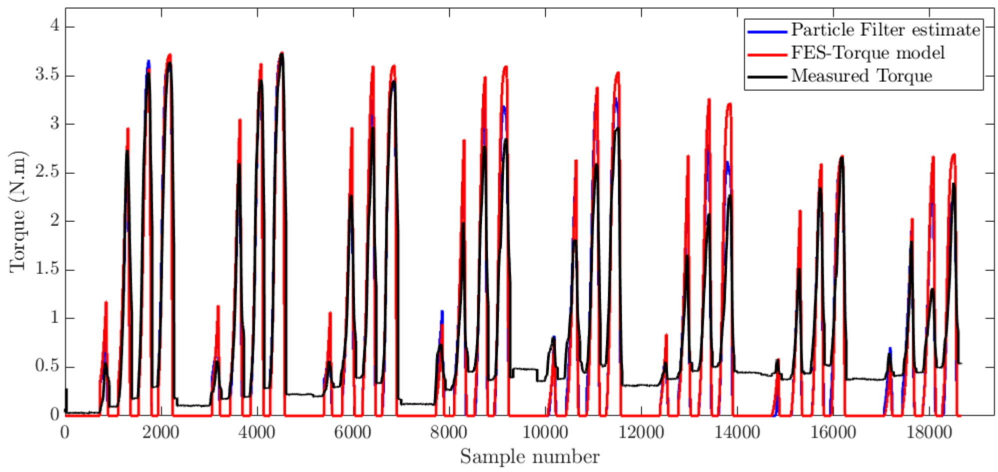

Fig. 6. FES-Torque estimation for Subject 3, Trial 1.

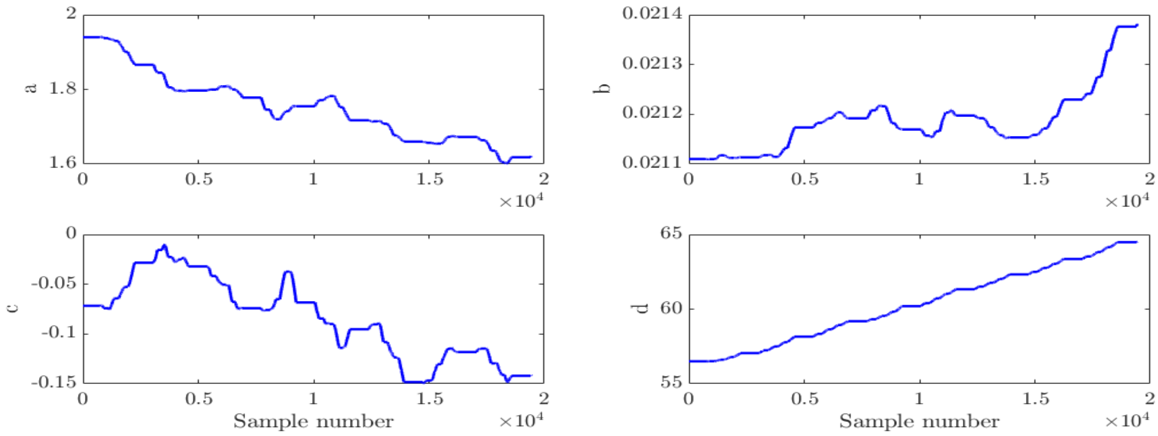

Fig. 7. Averaged FES-torque model parameters for Subject 1, Trial 2.

7. CONCLUSION

This study showed a simple logistic model can be used to estimate FES-induced torque, with a particle filter to update the model parameters to track the time-varying muscle response. The model can be easily inverted to determine the required stimulation for a desired assistive torque from FES. Future work will implement the FES-torque model into a hybrid assist-as-need controller for improved balancing of motor and FES assistance and better fatigue management, leading to improved rehabilitation.

ACKNOWLEDGEMENTS

Thanks to the HOPE Foundation for Research on Ageing in New Zealand for their financial support.

REFERENCES

Chatfield, L.T., Fortune, B.C., McKenzie, L.R., and Pretty, C.G. (2018). Implementation of a Particle Filter to Estimate Torque from Electromyography. *10th IFAC Symposium on Biological and Medical Systems (BMS 2018)*, 51(27), 327–332.

Chatfield, L.T., Fortune, B.C., McKenzie, L.R., and Pretty, C.G. (2019). Development of an Assist-as-need Controller for an Upper-limb Exoskeleton with Voluntary Torque Estimate. In *15th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications*. Los Angeles, USA.

De Luca, C. (1984). Myoelectrical manifestations of localized muscular fatigue in humans. *Critical reviews in biomedical engineering*, 11(4), 251—279.

del Ama, A.J., Gil-Agudo, n., Pons, J.L., and Moreno, J.C. (2014). Hybrid FES-robot cooperative control of ambulatory gait rehabilitation exoskeleton. *Journal of NeuroEngineering and Rehabilitation*, 11(1), 27.

Ha, K.H., Murray, S.A., and Goldfarb, M. (2016). An Approach for the Cooperative Control of FES With a Powered Exoskeleton During Level Walking for Persons With Paraplegia. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 24(4), 455–466.

Kirsch, N., Alibeji, N., and Sharma, N. (2017). Nonlinear model predictive control of functional electrical stimulation. *Control Engineering Practice*, 58, 319–331.

Li, Z., Guiraud, D., Andreu, D., Benoussaad, M., Fattal, C., and Hayashibe, M. (2016). Real-time estimation of FES-induced joint torque with evoked EMG: Application to spinal cord injured patients. *Journal of NeuroEngineering and Rehabilitation*, 13(1), 60.

Li, Z., Hayashibe, M., Zhang, Q., and Guiraud, D. (2012). FES-induced muscular torque prediction with evoked EMG synthesized by NARX-type recurrent neural network. In *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2198–2203. IEEE, Vilamoura-Algarve, Portugal.

McKenzie, L.R., Fortune, B.C., Chatfield, L.T., Stewart, A.M., and Pretty, C.G. (2018). Same-Electrode Stimulation and Recording With Dynamic Hardware Artefact Suppression. *10th IFAC Symposium on Biological and Medical Systems (BMS 2018)*, 51(27), 56–61.

Qin Zhang, Hayashibe, M., and Azevedo-Coste, C. (2013). Evoked Electromyography-Based Closed-Loop Torque Control in Functional Electrical Stimulation. *IEEE Transactions on Biomedical Engineering*, 60(8), 2299–2307.

Rong, W., Tong, K.Y., Hu, X.L., and Ho, N.S.K. (2012). Combined Electromyography(EMG)-driven robotic system with Functional Electrical Stimulation (FES) for rehabilitation. In *2012 38th Annual Northeast Bioengineering Conference (NEBEC)*, 313–314. IEEE, Philadelphia, PA, USA.

Rouhani, H., Same, M., Masani, K., Li, Y.Q., and Popovic, M.R. (2017). PID Controller Design for FES Applied to Ankle Muscles in Neuroprosthesis for Standing Balance. *Frontiers in Neuroscience*, 11, 347.

Thrun, S., Burgard, W., and Fox, D. (2002). *Probabilistic robotics*. MIT press.

Xu, W., Chu, B., and Rogers, E. (2014). Iterative learning control for robotic-assisted upper limb stroke rehabilitation in the presence of muscle fatigue. *Control Engineering Practice*, 31, 63–72.

Zhang, Q., Hayashibe, M., Fraisse, P., and Guiraud, D. (2011). FES-Induced Torque Prediction With Evoked EMG Sensing for Muscle Fatigue Tracking. *IEEE/ASME Transactions on Mechatronics*, 16(5), 816–826.