The gap in functional electrical stimulation simulation

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***Abstract*—Functional electrical stimulation (FES) applies low-current high-voltage electrical pulses to muscles to induce a torque-generating contraction. While FES is widely used for movement rehabilitation, it is challenging to control the muscle response for goal-oriented actions, due to the many physical and neural sources of variation in the signal-to-muscle response pathway. This paper aims to describe sources of variation that have not previously been discussed for learning FES control, and proposes how a neuromuscular simulation might leverage this knowledge through domain randomisation to help develop adaptive real-world controllers.**

***Index Terms*—Electrical stimulation, robot control, human in the loop, machine learning, digital simulation**

I. Introduction

Control of the neuromuscular system can be assisted by electrical stimulation of muscle fibres through the skin using functional electrical stimulation (FES), a commonly used technology in neurorehabilitation of motor deficits [1].

Actuating the human neuromuscular system with FES for goal-directed movements is a non-trivial task. Goal-directed movements typically require intricate coordination of joint movements through activation of multiple muscle groups. Furthermore, the muscles' response to electrical stimulation is affected by many complex and time varying factors.

Given the many variables that introduce uncertainty to the control of an FES system, data-driven models are a favoured approach. Nevertheless, neuromuscular responses to FES is largely person and case specific. Furthermore, there exists many non-linear, non-stationary characteristics that are modulated by unobservable factors that would necessitate an unrealistically large dataset to model using experimental data.

Simulation-based learning for FES control has been explored to address the challenge of data scarcity, but challenges remain in transferring policies learned in simulation to real-world systems [2]. The focus of this paper is to identify the main sources of variability inherent in FES control, and discuss how these variations might be incorporated to a domain randomisation learning protocol, such that we may effectively translate simulated neuromuscular systems into real-world FES control applications. It is intended that by effectively incorporating these sources of variance and uncertainty into simulations, we would enable more robust transfer of policies person-to-person without requiring extensive retraining or calibration, presenting greater opportunities for FES-based rehabilitation and assistance at home.

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II. Neuromuscular Model for FES Control

For transferring simulated policies to real-world biological systems, it is useful to identify sources of uncertainty and variance apparent in the FES control, as this system knowledge can be used to design domain randomisation strategies that focus on biologically feasible regions, and improve the subsequent learning-based control models.

Recent work studying FES elbow joint control precedes real-world control with a simulation stage [2]. Here, while fatigue is explicitly modelled using a recurrent neural network, a drop in performance is still observed when transferring the learned policy to the real musculoskeletal system, though still produces more stable control than a conventional PID controller. This drop in performance is likely a result of training in a simulation that uses a fixed-parameter biomechanical model of the human arm, i.e. the real-world variations described below are not factored into the learned model.

For assisting complex motions such as dexterous grasping with FES, we can consider two primary groups of system variables; *stationary* and *non-stationary* variables. Stationary system variables are those whose behaviour do not vary over the typical course of an FES session, whereas non-stationary variables may see significant changes in their properties in a relatively short time frame (Fig. 1).

A. Stationary Variables

The main system variables that are stationary during use of an FES system include the adopted stimulation profile, and the underlying musculoskeletal system.

Here, the stimulation profile refers to the quantity and placement of stimulation electrodes, the stimulation patterns, amplitudes and frequencies selected, and the physical dimensions of the stimulation electrodes. These properties are distinct from the resulting response in the underlying muscle. Many current FES studies consider large muscle groups with large stimulation electrode pads to encourage signal propagation through the muscle, such that more muscle fibres are engaged. While this offers benefits in the muscle output power, there is a loss in specificity that might be required for finer control activities such as dexterous manipulation. Using an array of smaller electrodes enables finer control of muscle fibres; however, this introduces a combinatorial optimisation problem to the challenge of FES control, given the redundancy present in the musculoskeletal system, and the diffuse activation produced by an electrode resulting in the stimulation of unintended fibres. Smaller electrodes may also lead to increased discomfort due to higher charge densities on the skin, limiting the level of stimulation that can be delivered by an electrode.

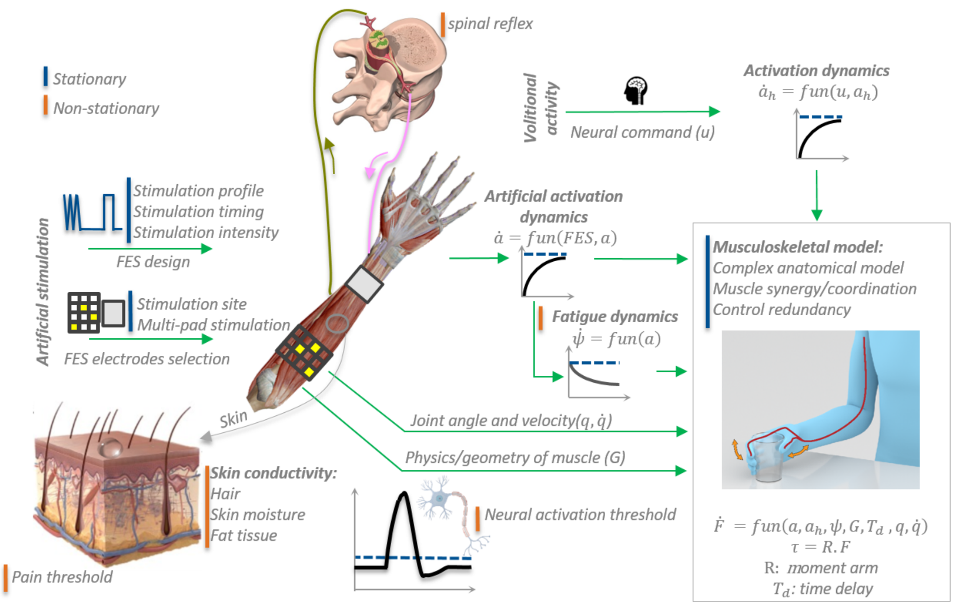

Fig. 1. Neuromuscular dynamics in response to artificial electrical stimulation. A map between FES electrodes position/intensity and joint torque may be learned while considering both stationary and non-stationary sources of variation.

The musculoskeletal system then concerns the anatomy of the person that FES is being applied to. There is a degree of uncertainty in the exact location of specific muscles, as well as variable skin-to-muscle depths in the subcutaneous tissue that will affect propagation of the FES stimulation. The anatomical size, mass, and layout of muscles, tendons and bones will vary person-to-person, affecting the dynamic response of joints and limbs to a stimulation, but this will not vary over the course of an FES session.

B. *Non-Stationary Variables*

There are many non-stationary variables to account for in FES control. The main variables of interest here are muscle fatigue, pain threshold, reflexes, activation thresholds, and skin surface conductance conditions.

Existing works in the field of traditional control have considered this non-stationarity through non-linear model-free control methods [3]–[5]. Recently, reinforcement learning (RL) based control for elbow joint control modelled fatigue in a simulated experiment as a time varying activation scaling parameter [6], while a separate study modelled fatigue as a partially observable state that can be modelled as a fully observable state by learning the hidden state through the use of a recurrent network structure [2].

Muscle fatigue is perhaps the most obvious non-stationary variable to consider for control adaptation, there is a clear drop-off in output muscle torque for a sustained stimulation; however, this effect is relatively short term. Other sources of non-stationary in the muscle response, such as the acceptable pain threshold [7], [8], or skin surface conductance levels [9], may take longer to become apparent than muscle fatigue, but the effects on control will persist for a longer duration.

III. Simulation and Domain Randomisation for Learning FES Control

Typically, machine learning techniques for human behaviour modelling treat the human as a black-box model where all the sources of variability are introduced as noise. Given the sparse neuromuscular FES-response data available in real-life FES applications, explicitly introducing prior knowledge on the distribution of the data can decrease the uncertainty inherent in the learnt models. For instance, Medina et al. [10] designed Gaussian Process priors to generate a latent desired trajectory that echoes human-like mechanical impedance behaviour to improve the predictive capability of the machine learning algorithm. Prior works in domain randomization have identified the challenge of designing simulation parameter distributions that align well to policies executed in real environments [11], and how careful consideration of real-world data can lead to better randomization distributions for simulator parameters, leading to more robust real-world policies [12].

Given the wide range of variations that may affect FES control, the challenge of gathering data and training on a person for extended periods, and the combinatorial challenge in identifying stimulation patterns for FES-array systems and multi-joint movements, we believe there is a clear case for applying Sim2Real methodologies such as domain randomisation to learning FES control. Furthermore, by accounting for the stationary and non-stationary variables described here, it would be possible to develop robust and transferable RL-derived policies that enable real-world FES rehabilitation and assistance at home.

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