Model-based Fusion of Surface Electromyography with Kinematic and Kinetic Measurements for Monitoring of Muscle Fatigue

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ABSTRACT

This study proposes a novel method for monitoring muscle fatigue using muscle-specific dynamic models which relate joint time-frequency signatures extracted from the relevant electromyogram (EMG) signals with the corresponding estimated muscle forces. Muscle forces were estimated using physics-driven musculoskeletal models which incorporate muscle lengths and contraction velocities estimated from the available kinematic and kinetic measurements. For any specific individual, such a muscle-specific dynamic model is trained using EMG and movement data collected in the early stages of an exercise, i.e., during the least-fatigued behavior. As the exercise or physical activity of that individual progresses and fatigue develops, residuals yielded by that model when approximating the newly arrived data shift and change because of the fatigue-induced changes in the underlying dynamics. In this paper, we propose quantitative evaluation of those changes via the concept of a muscle-specific Freshness Index (FI) which at any given time expresses overlaps between the distribution of that muscle's model residuals observed on the most recently collected data and the distribution of modeling residuals observed during non-fatigued behavior. The newly proposed method was evaluated using data collected during a repetitive sawing motion experiment with 12 healthy participants. The performance of the FI as a fatigue metric was compared with the performance of the instantaneous frequency of the relevant EMG signals, which is a more traditional and widely used metric of muscle fatigue. It was found that the FI reflected the progression of muscle fatigue with desirable properties of stronger monotonic trends and smaller noise levels compared to the traditional, instantaneous frequency-based metrics.

1. INTRODUCTION

Muscle fatigue results from a sequence of processes in the nervous system and the muscle fibers which reduce neural drive to the muscle and/or impair the muscle's contractile mechanism (Taylor, Amann, Duchateau, Meeusen, & Rice, 2016). For healthy individuals performing strenuous or prolonged activities (laborers, athletes, soldiers etc.), muscle fatigue limits task efficiencies and performance, causes adverse sensations such as muscle pain and/or perception of increased effort, and in some occasions could lead to changes in biomechanical function which increases the risk of injury (Mizrahi, Verbitsky, & Isakov, 2000; Parijat & Lockhart, 2008; Taylor et al., 2016; Weist, Eils, & Rosenbaum, 2004). Furthermore, for individuals affected by disorders caused by neurological or muscular diseases, or aging, muscle fatigue is increased and restricts daily life (Taylor et al., 2016). Therefore, quantitative understanding, modeling and monitoring of muscle fatigue is of utmost importance for devising appropriate training plans for athletes (Ament & Verkerke, 2009), design and optimization of rehabilitation procedures (Bonato, Roy, Knaflitz, & De Luca, 2001), prevention of fatigue-induced injuries, as well as reductions of occupational hazards.

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Traditionally, monitoring of muscle fatigue has been conducted by detecting and quantifying fatigue induced changes in the electromyography (EMG) signals of the relevant muscles (Bonato et al., 2001; Cifrek, Medved, Tonković, & Ostojić, 2009; Dimitrov et al., 2006; Karlsson, Yu, & Akay, 2000), or in the relevant kinematic and/or dynamic variables characterizing movements of the investigated person (Gholami, Napier, Patiño, Cuthbert, & Menon, 2020; Karg, Venture, Hoey, & Kulic, 2014; Karvekar, Abdollahi, & Rashedi, 2021; Sedighi Maman et al., 2020; Whelan, O'Reilly, Ward, Delahunt, & Caulfield, 2016). EMG-signal based tracking of muscular fatigue is based on the fact that as muscular fatigue progresses, both the firing frequency of the motor units and the muscle fiber conduction velocity are reduced, which causes the spectrum of the relevant EMG signals to shift towards lower frequencies as fatigue progresses (Contessa & De Luca, 2013; De Luca & Hostage, 2010; Merletti & Farina, 2016; Taylor et al., 2016). Consequently, various EMG-signal based metrics were proposed as indicators of muscle fatigue, including frequency-domain metrics, such as the median and mean power frequency (Cifrek et al., 2009) and spectral indices (Dimitrov et al., 2006), as well as joint time-frequency-domain metrics, such as the instantaneous frequency (Bonato et al., 2001; Karlsson et al., 2000). Furthermore, when muscle fatigue occurs, movement strategies (Karg et al., 2014), leading to muscle fatigue monitoring strategies based on the changes of the relevant kinematic signatures, including but not limited to accelerations (Karvekar et al., 2021; Whelan et al., 2016), joint angles (Karg et al., 2014; Sedighi Maman et al., 2020; Whelan et al., 2016) and angular speeds (Karvekar et al., 2021; Whelan et al., 2016), or gait parameters during walking, such as stride length and time (Gholami et al., 2020; Sedighi Maman et al., 2020).

Whether using EMG features or kinematic and dynamic signatures, the above-mentioned approaches can be seen as muscle fatigue monitoring methods that use a purely signal-based paradigm for monitoring the system condition (Alaswad & Xiang, 2017). Signal-based monitoring associates the underlying system condition with the system outputs in the sense that anomalous system behavior is associated with observing anomalous outputs from the system. An underlying assumption associated with this paradigm is that the system inputs and environment are stationary. This, however, is an unrealistically restrictive assumption when monitoring highly complex dynamic systems, such as the human musculoskeletal systems, where highly variable muscle activities (R. A. Miller, Thaut, McIntosh, & Rice, 1996) and motion patterns (Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995) usually occur. This greatly limits the applicability of purely signal-based methods in monitoring muscle fatigue, especially during long-term and highly dynamic activities.

As an alternative to the signal-based paradigm, the so-called system-based condition monitoring paradigm utilizes both inputs and outputs of a system to construct and track dynamic relationships between them (Isermann, 2011). Tracking the changes of the relationship between the system inputs and output instead of the changes of only the output enables monitoring of systems that undergo highly variable operating regimes with a wide spectrum of inputs. Therefore, the stationary input assumption is no longer required in the system-based paradigm. Consequently, system-based approaches have seen numerous applications in monitoring of systems that undergo highly dynamic operating regimes, such as automotive engine systems (Cholette & Djurdjanovic, 2012; Liu, Djurdjanovic, Marko, & Ni, 2009), electricity generators (Djurdjanovic, Hearn, & Liu, 2010), robotics (Bryant, 2014; Costuros, 2013) and manufacturing systems (Shi, 2006).

Recently, the system-based monitoring paradigm also gained attention in the domain of monitoring of muscular fatigue during human body movements and this paper can be seen as a contribution to the research in that direction. In the next section, we offer a brief review of the state-of-the-art in system-based monitoring of muscular fatigue and outline unique contributions of the novel research presented in this paper. As will be shown, the previous system-based monitoring of muscular fatigue faced challenges in establishing muscle-specific fatigue indicators, as it relied on purely data-driven modeling of dynamics between readily measurable signals, which mean that muscles forces, which are not readily measurable, could not be considered. To address this challenge, in this work, we combine data-driven approaches with physics-based musculoskeletal models to formulate and track muscle-specific dynamic models relating the EMG signals and the corresponding estimated muscle forces.

2. REVIEW OF PRIOR RESEARCH IN SYSTEM BASED APPROACHES TO MONITORING OF MUSCULAR FATIGUE

The earliest work pursuing system-based paradigm for monitoring of muscular performance can be found in (Musselman, Gates, & Djurdjanovic, 2016), where musculoskeletal dynamics was modeled using vectorial autoregressive models with exogenous inputs (vARX model) [1] , which took the instantaneous intensity and frequency features from relevant EMG signals as model inputs, while angular velocities of the joints involved in the motion were as the outputs. For each participant in the study, the vARX model describing his/her musculoskeletal dynamics in its fresh, non-fatigued condition was built using

[1] vARX models are essentially linear dynamic models relating inputs and outputs of a system.

the EMG and limb motion data observed in the earliest stages of the exercise, while degradation in the musculoskeletal performance was quantitatively evaluated by tracking changes in the distributions of the residuals of that model which occurred as each participant's exercise progressed. In a later study (Musselman, Gates, & Djurdjanovic, 2017), the authors analyzed the same dataset as the one used in (Musselman et al., 2016), but with a significant improvement in the sense that the study reported in (Musselman et al., 2017) took into account inherent non-linearities in the dynamics of human body motion by replacing the vARX models from (Musselman et al., 2016) with non-linear dynamic models relating instantaneous EMG intensities and frequencies to the joint angular velocities. Specifically, the study reported in (Musselman et al., 2017) used the so-called Growing Structure Multiple Model System (GSMMS) (Cholette & Djurdjanovic, 2012) models to represent musculoskeletal dynamics. This was motivated by the capability of those "divide-and-conquer" type models[2] to elegantly identify situations in which model inputs significantly differ from those observed during the model-building process. Consequently, GSMMS models used in (Musselman et al., 2017) enabled detection of situations in which participants, consciously or subconsciously, changed the way they were executing the pre-described motion, leading to unusual EMG patterns unseen during the model-training process. Regardless of the model form, model predictions in such "untrained" situations cannot be trusted to reflect the behavior of the actual system and, consequently, large modeling residuals observed in those situations can lead to false alarms. The ability of the GSMMS models to detect such situations and avoid outputting the corresponding monitoring results led to smoother, more intuitive fatiguing curves than what was observed in (Musselman et al., 2016).

Unfortunately, the dataset used in (Musselman et al., 2016) and (Musselman et al., 2017) corresponded to only one fatiguing cycle of each participant, i.e. it did not contain data related to the resting process and repeated fatiguing cycles. This motivated the study in (Xie & Djurdjanovic, 2019), where the authors measured EMG signals of relevant muscles and the corresponding forces/velocities associated with fatiguing and resting during lower limb muscle isometric contraction, as well as during a cyclic motion involving the temporomandibular joint (TMJ). In both cases, vARX models were used to describe the relevant system dynamics and, in both cases, system dynamics described by those models showed remarkably consistent recoveries after the participants rested. Similar recovery behavior over a longer time span has also been observed in (Madden, Djurdjanovic, & Deshpande, 2018), where a study of arm muscle fatigue during the use of a spacesuit glove was reported. In addition, the study in (Madden et al., 2018) involved activities with two different load settings – one with the glove being powered on, and another one involving the same motion performed with the unpowered glove. Results clearly showed faster-developing and more pronounced fatiguing process when the task loads were higher, i.e. when the glove was not powered, as opposed to when the same participants did the same tasks, but with a powered glove.

The above mentioned investigations were further extended in (Yang, Nicolini, Kuang, Lu, & Djurdjanovic, 2019) by tracking the fatigue and recovery process of a grasping task over multiple days using the skin-compliant tattoo-like sEMG sensors described in (Kabiri Ameri et al., 2017). These sensors enable a close electrode-to-skin contact and, unlike traditional EMG electrodes, can be left on the skin of a person over multiple days without causing irritation or intrusion, which greatly reduces sensor-to-noise ratio associated with EMG sensing (Kabiri Ameri et al., 2017). The study was conducted across multiple days, with three types of trials: repetitive trials within the same day, repetitive trials across multiple days and repetitive fatigue and recovery trials. Throughout all trials and across multiple subjects, consistent patterns of system degradation and system recoveries were observed during the exercising and recovery portions of the trials, respectively.

However, even though model-based fatigue metrics reported in all the previously discussed papers clearly show intuitively plausible patterns consistent with muscular fatigue and recovery, a quantitative relationship between newly proposed system-based condition-monitoring metrics of muscle fatigue, and more traditional and widely accepted metrics of muscular fatigue was established only recently. Namely, in (Madden, Djurdjanovic, & Deshpande, 2021), the authors report the first study in which a strong quantitative connection was established between fatigue metrics yielded by the system-based monitoring approach and two traditionally utilized measures of fatigue - the maximum voluntary contraction force and the ratings of perceived exertion (Madden et al., 2021). These findings further corroborated the viability of using the system-based monitoring paradigm for continuous quantitative assessment of muscle fatigue.

One should note at this point that all prior studies in the realm of system-based monitoring of muscular fatigue relied on purely data-driven models of the relevant system dynamics. In those studies, the underlying models were built using only signatures that could be obtained from readily measurable signals, which included (1) EMG sensor readings and (2) the corresponding limb kinematic/force variables estimated from trajectories of motion tracking markers and external forces

[2] The divide-and-conquer type models tackle the challenge of model nonlinearity by partitioning the input space of the model into a set of disjoint regions, with a relatively simple local model describing the system dynamics within each of those regions. In particular, the GSMMS model performs the partitioning of the input space using a Fritzke's growing gas based growing self-organizing network (Fritzke, 1994), which creates clusters of inputs in an unsupervised manner, while locally linear dynamic models are fit inside each cluster.

measured during a person's motion. Actual muscle forces were not among the variables considered in (Madden et al., 2018, 2021; Musselman et al., 2016, 2017; Xie & Djurdjanovic, 2019; Yang et al., 2019) simply because those forces cannot be readily obtained in a non-intrusive way, especially during movement and exercises. On the other hand, from a purely physiological perspective, a dynamic model of the forces any individual muscle produces as a response to neural excitation would be a much more direct reflection of its performance and fatigue condition, simply because the limb kinematics and forces are inherently a result of a combination of multiple muscle forces moving the body. Hence, there could be significant potential benefits if one could utilize the readily available sensor readings, such as trajectories of motion tracking markers and external forces observed during one's motion, to estimate the relevant muscle forces which led to those movements, based on which a more immediate system-based approach to monitoring of individual muscle-specific fatigue could be pursued. This paper aims to exploit the aforementioned opportunity.

To that end, various physics and physiology driven muscular and musculoskeletal models provide foundations for the estimation of muscle-related variables that are otherwise challenging to measure. One of the most commonly used forms of muscle models is the so-called Hill-type muscle model form (Hill, 1938; R. H. Miller, 2018; Zajac, 1989). In these models, force produced by a muscle is considered to be dependent on the summed motor unit action potentials of that muscle, as well as the corresponding muscle length and contraction velocity. During movement, EMG electrodes can be used to non-intrusively obtain measurements of the summed motor unit action potentials of a muscle. Nevertheless, the corresponding muscle lengths, contraction velocities and associated forces cannot be measured directly and non-intrusively as the movements take place. Instead, muscle lengths and contraction velocities as well as the corresponding muscle forces can be estimated from the available limb movement and force measurements using physics-driven musculoskeletal models (Caruthers et al., 2016; Gomes, Ackermann, Ferreira, Orselli, & Sacco, 2017; Ng, Mantovani, Modenese, Beaule, & Lamontagne, 2018; Trinler, Schwameder, Baker, & Alexander, 2019). Typical musculoskeletal models describe the kinematics and dynamics of human limb movements by approximating bones as rigid segments connected by joints and muscles, with muscles being modeled as tensile actuator elements (Bassani & Galbusera, 2018). The governing equations in such musculoskeletal models are the physics-based dynamic equations of motion which link the limb and joint kinematics and geometries with the muscle forces and external loads on the body. Based on those governing equations, inverse dynamics can be used to estimate the hard-to-measure lengths, contraction velocities and forces of the relevant muscles from the relatively easily available measurements of external forces acting on the body, and limb geometries and kinematics characterizing the motion (Anderson & Pandy, 2001). Together with measurements of EMG signals, estimates of muscle lengths and contraction velocities provide inputs for Hill-type models of individual muscles during motion, while estimates of individual muscle forces provide the corresponding model outputs. Thus, physics-based musculoskeletal models of relevant movements can be used to convert readily available measurements of EMG activity and kinematic and dynamic variables into inputs and outputs of muscle-specific dynamic models, based on which performance and degradation of individual muscles could be tracked during movement using the system-level condition monitoring paradigm.

To that end, the aim of this study is to facilitate improved system-based monitoring of muscle fatigue through a merger of data-driven dynamic modeling and monitoring methods with physics-based musculoskeletal models. Improvements in the performance of the newly constructed fatigue metric will be evaluated through comparison with the traditional, EMG-based muscle fatigue indicators. The remainder of this paper is structured as follows. Section 3 describes the novel system-based approach to monitoring of muscle-specific fatigue levels and the setup of the experimental case study in which the new method is evaluated. Section 4 presents the results of applying the proposed method to monitoring of muscle fatigue and compares its performance to the results obtained using a traditional EMG-signal based fatigue indicator. Finally, summary of the finding of this work and several directions for possible future research are enclosed in Section 5.

3. METHODS

3.1. General Method Description

The proposed system-based approach for monitoring of muscle fatigue tracks the changes in individual muscle dynamics based on the available measurements of limb movements and external forces. Inspired by the Hill-type muscle models (Hill, 1938; Zajac, 1989), we describe the dynamics of each individual muscle using a model whose inputs are muscle lengths and contraction velocities, as well as selected key signatures characterizing the electrical excitations associated with that muscle, while model outputs are the corresponding muscle forces. Figure 1 shows an overview of the data and models used in the proposed approach. Details of the data and the models involved are described in the remainder of this subsection.

Electrical activities associated with muscle excitation can be continuously sensed during motion using EMG electrodes. Such measurements are well-known to be highly noisy and non-stationary (Musselman et al., 2016), which is why all EMG signals were first transformed into their binomial-kernel based joint time-frequency distributions [3] (TFDs) (Jeong & Williams, 1992). Instantaneous intensities and instantaneous frequencies were then extracted from EMG TFDs and used as muscle-activity related inputs into the Hill-type muscle models because of their well-documented relationship with the corresponding muscle forces (Marieb & Hoehn, 2007) and muscle fatigue (Bilodeau, Schindler-Ivens, Williams, Chandran, & Sharma, 2003; Potvin, 1997).

In order to transform trajectories of motion tracking markers and external forces measured during a person's motion into estimates of the corresponding muscle-specific lengths, contraction velocities and forces [4], we use the inverse dynamics procedure based on the physics-based musculoskeletal model of the relevant motion. Specifically, for each participant, individualized geometries for that person's musculoskeletal model are obtained by scaling a generic form model to match the participant's anthropometry, as described in (Delp et al., 2007). Based on those geometries, trajectories of joint rotations are calculated using the weighted least-squares based inverse kinematics procedure, which determines the joint rotations that most accurately reproduce the trajectories of motion tracking markers. Finally, based on the joint rotations and model geometries, muscle lengths and muscle contraction velocities can then be calculated. The corresponding muscle forces are estimated through the so-called *static optimization* procedure which finds a set of muscle forces that can produce the joint rotations, while minimizing some physiologically-inspired cost function (Anderson & Pandy, 2001). Following (Anderson & Pandy, 2001), in this paper we pursue this step via minimization of the sum of squared muscle activations, which hypothesizes that the neuromuscular system minimizes the amount of neuromuscular activations to achieve muscular contractions. Other cost functions, such as the sum of muscle forces, the sum of muscle stresses, or the metabolic cost on the muscles, can also be used. A comprehensive review of different cost functions used in static optimization for estimating muscle forces can be found in (Erdemir, McLean, Herzog, & van den Bogert, 2007).

Following Musselman et al. (Musselman et al., 2017), in order to capture the least degraded dynamics of muscle q for person p, the GSMMS model $M_{p,q}$ was built using data collected at the beginning of the person's exercise (the initial part of each person's exercise), during which the muscle's performance is believed to be the least degraded. Inputs into these data driven models were the instantaneous intensities and frequencies extracted from the relevant EMG signals, as well as the estimated muscle lengths and the contraction velocities, while the model outputs were the muscle forces estimated using physics-based musculoskeletal modeling. The term *modeling residual* in this modeling setup, therefore, refers to the difference between the muscle forces predicted by the GSMMS model and the muscle forces estimated using musculoskeletal modeling. The model $M_{p,q}$ built in this least degraded state will be referred to as the "fresh model", and the data used to train it will be referred to as the "fresh data". Let $D_{p,q}^{Fresh}$ denote the distribution of modeling residuals produced by the fresh model $M_{p,q}$ on the fresh dataset. As the exercise progresses and new data arrive, the distribution of the most recently observed modeling errors produced by the fresh model $M_{p,q}$ can be generated. Let us denote this distribution by $D_{p,q}^{T}$, where T denotes the time interval over which the performance of muscle q for person p is evaluated, i.e., the time interval over which the distribution $D_{p,q}^{T}$ of modeling errors produced by the fresh model is evaluated. If the dynamic behavior of muscle q for person p during the time interval T is the same or similar to that observed on the fresh data, the distributions $D_{p,q}^{Fresh}$ and $D_{p,q}^{T}$ should be similar to each other. However, if the muscle dynamics in the interval T have changed compared to those observed on the fresh data, due to, e.g. fatigue or injury, the distribution $D_{p,q}^{T}$ will be different from the fresh distribution $D_{p,q}^{Fresh}$.

This discrepancy between the template distribution of modeling residuals $D_{p,q}^{Fresh}$ and the distribution $D_{p,q}^{T}$ generated by the fresh model $M_{p,q}$ during time-interval T can be quantified and used to track the degradation of the muscle condition. Following (Musselman et al., 2017), the similarity between the two distributions is evaluated using the Matusita's coefficient of overlap between two distributions (Matusita, 1955), expressed in the form

$$SFI_{p,q}^{T} = \int \sqrt{D_{p,q}^{Fresh}(x) D_{p,q}^{T}(x)}\,dx \tag{1}$$

where the overlap coefficient $SFI_{p,q}^{T}$ will be referred to as the System Freshness Index (SFI) for muscle q of person p, observed during the interval T. Please note that SFI coefficients can range between 0 and 1, with 1 indicating a perfect match between the two distributions of modeling residuals, and thus a perfect match between the fresh and most recently observed muscle dynamics. Other symmetric and bounded measures of the overlap/distance between two distributions, such as the Jenson-Shannon divergence, may also be used for defining the SFI metrics. A comprehensive survey of such metrics can be found in (Cha, 2007).

To evaluate the performance of the newly proposed fatigue metric, we compared it to the performance of a muscle fatigue index based on the instantaneous frequency of EMG signals, which is widely seen as a traditional EMG-based muscle

[3] Binomial kernel is a signal independent member of the so-called reduced interference distribution family of Cohen's class time-frequency kernels (Jeong & Williams, 1992). The signal independent nature of this kernel enables a faster calculation of time-frequency distributions compared to signal dependent kernels, while delivering the favorable mathematical properties, including signal filtration based on the suppression of the so-called time-frequency cross-terms (Cohen, 1995).

[4] As mentioned earlier, estimated muscle lengths, contraction velocities and extracted EMG signatures form inputs for the Hill-type muscle models, while estimated muscle forces constitute outputs of those models.

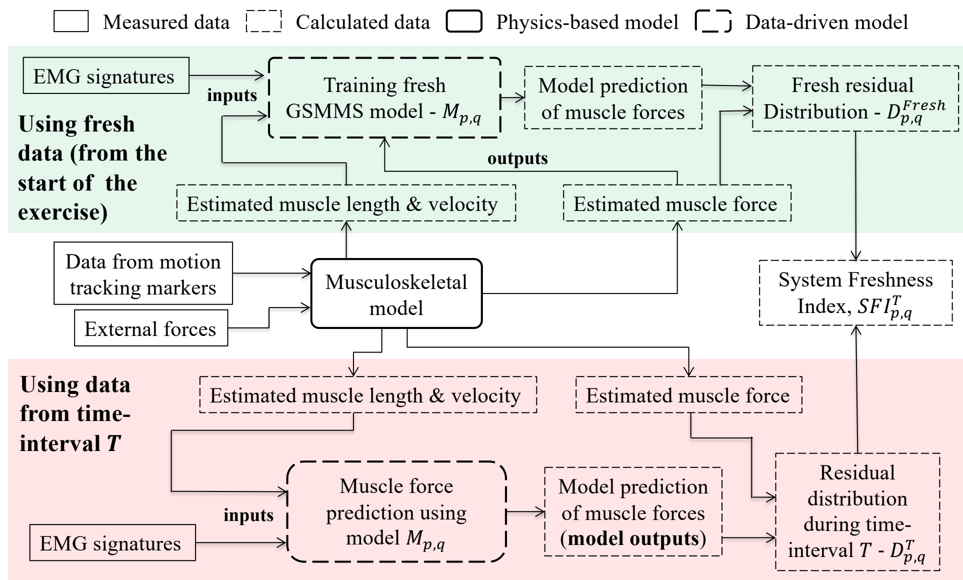

Figure 1: Data and models used in the proposed system-based monitoring approach.

fatigue indicator (Bonato et al., 2001). Let $F_{p,q}^{Fresh}$ denote the distribution of the instantaneous EMG frequencies in the fresh dataset and let $F_{p,q}^{T}$ denote the distribution of the instantaneous frequencies during some interval T. Following the way we introduced the system-based fatigue indices in (1), let us define the purely EMG based fatigue index for muscle q of person p during time interval T using the Matusita's overlap coefficient,

$$EFI_{p,q}^{T} = \int \sqrt{F_{p,q}^{Fresh}(x) F_{p,q}^{T}(x)} dx \qquad (2)$$

Once again, one should note that the EMG-based Freshness Index (EFI) defined by (2) can take values between 0 and 1, with 1 indicating a perfect match between the two distributions of instantaneous EMG frequencies, and thus lack of fatigue-induced changes relative to the template distribution $F_{p,q}^{Fresh}$.

The force recorded during fatigue produced by repeated tetanic stimulation of individual muscle fiber shows a progressive declining trend (Allen, Lamb, & Westerblad, 2008). This suggests a well-behaved fatigue index should show a monotonic trend over time, depicting progression of fatigue-induced changes in the corresponding muscle's behavior away from its fresh performance. Following this logic, in this study, we used the one-tailed Mann-Kendall test for monotonic trends (Kendall, 1948) to statistically assess ($p < 0.05$) existence of monotonic trends over time in the SFI and EFI indices.

In addition to the monotonicity, we also compared the levels of noise in the fatigue indices generated from the system-based and signal-based approaches. Let $\{FI_i; i = 1, \ldots, n\}$ denote a time-series of fatigue indices, where n is the number of elements of the time series. We assessed the relative noise level at sample i of that time-series using the quantity $\epsilon_i = \frac{|FI_i - \widehat{FI}_i|}{\widehat{FI}_i}$, where $\widehat{FI}_i$ denotes the denoised value of the time-series sample i, which was obtained by applying a simple moving average to the time-series $\{FI_i; i = 1, \ldots, n\}$. Then, for each muscle of each participant in the study, a one-tailed two-sample t-test ($p < 0.05$) was used to test if the relative noise of the system-based SFI indices, $\{\epsilon_i^{sys}; i = 1, \ldots, n\}$, was smaller than or equal to the relative noise of the purely EMG-based indices EFI, $\{\epsilon_i^{EMG}; i = 1, \ldots, n\}$.

3.2. Description of the Experiment

The data used for muscle fatigue monitoring was collected from 12 healthy individuals who performed a repetitive sawing motion. The experiment and collected data are originally described in the previous study by Gates and Dingwell (Gates & Dingwell, 2008) and the data were used in (Musselman et al., 2016, 2017) for system-based monitoring of the performance of the neuromusculoskeletal system using purely data-driven dynamic models. The following will offer the essential information in the exercise protocol, as well as the kinematic, kinetic and EMG measurements in this study, while a more detailed description can be found in (Gates & Dingwell, 2008).

As illustrated in Figure 2, subjects were seated in a high-back chair with a belt to restrain the trunk movement. They were directed to push and pull a handle attached to a weight stack over a low-friction metal track in the anterior-posterior direction until voluntary exhaustion. The weight stack was adjusted for each subject to be 15% of their maximum isometric pushing/pulling strength. The frequency of the movement was guided by a metronome, whose frequency was approximately 1 Hz and was fixed during the movement.

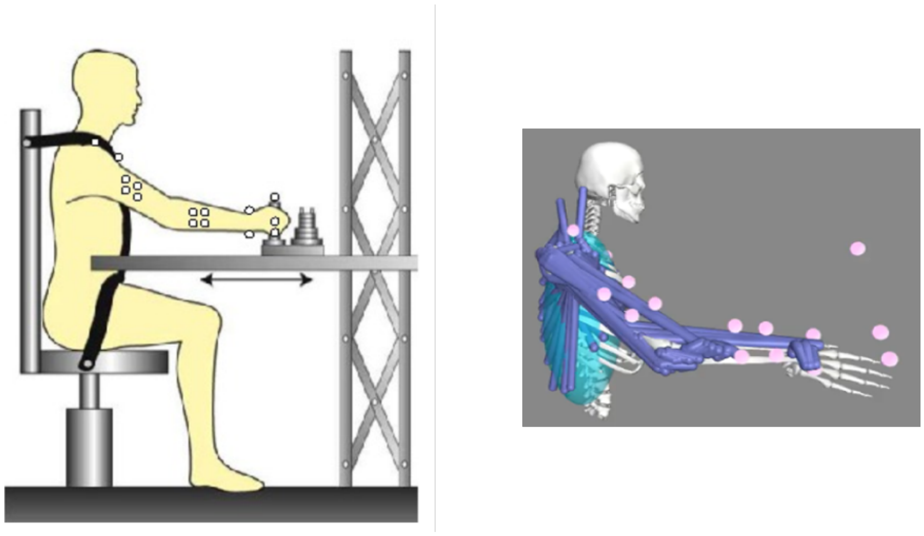

Figure 2: The left plot shows schematic illustration of the repetitive sawing motion (left) (Gates & Dingwell, 2008), while the right plot illustrates the corresponding musculoskeletal model rendered by the Opensim 4.0 software (Delp et al., 2007). White circles on the left plot represent the kinematic markers used to track the subject's motion via motion capture system, while pink circles on the right plot are the corresponding virtual markers defined in the musculoskeletal model.

For kinematic measurement, sixteen reflective markers were placed on the participant's trunk, upper arm, lower arm and hand to track the movement of each body segment. An extra marker was placed on the handle to determine the motion cycle. The spatial position of these markers was collected at 60 Hz by an eight camera Vicon-612 motion analysis system (Oxford Metrics, Oxford, UK), while the forces and moments exerted on the handle were concurrently measured by a six-axis load cell (JR3 Inc., Woodland, CA, USA) mounted at the base of the handle. The EMG signals of the arm and torso muscles of each participant were recorded at 1,080 Hz using a Delsys Bagnoli-8 (Delsys Inc., Boston, MA, USA) system and were integrated with the Vicon-612 motion measurements. The main muscles involved in the exercise are the middle trapezius (MT), pectoralis major (PM), anterior deltoid (AD), lateral deltoid (LD), posterior deltoid (PD), triceps (T), and biceps (B).

An upper extremity musculoskeletal model called Dynamic Arm Simulator (Blana, Hincapie, Chadwick, & Kirsch, 2008) was used in this study for estimating the muscle lengths, muscle contraction velocities and muscle forces during the sawing motion. The model comprises seven body segments, including thorax, clavicle, scapula, humerus, ulna, radius and hand. The eleven degrees of freedom in the model are distributed in the sternoclavicular, acromioclavicular and glenohumeral joints, elbow flexion-extension and forearm pronation-supination. A total of 29 shoulder and arm muscles are modeled, including all the muscles described in the previous paragraph. The model was verified by comparing estimated muscle activations to EMG signals recorded from the shoulder and arm muscles (Blana et al., 2008). Subject-specific scaling of model geometries was performed in Opensim 4.0 (Delp et al., 2007), while inverse kinematics, inverse dynamics and static optimization stages were conducted using Opensim 4.0 API with MATLAB for automatic processing.

4. RESULTS AND DISCUSSION

The SFI for each of the 84 muscles from the 12 subjects displayed a statistically significant ($p < 0.05$) monotonically decreasing trend, as per Mann-Kendall tests. On the other hand, the EFI of 15 muscles (17.86% of the total of 84 analyzed muscles) failed to show statistically significant monotonically decreasing trends. Figure 3 shows detailed results of statistical monotonicity tests for EFI metrics obtained for all muscles and all 12 subjects.

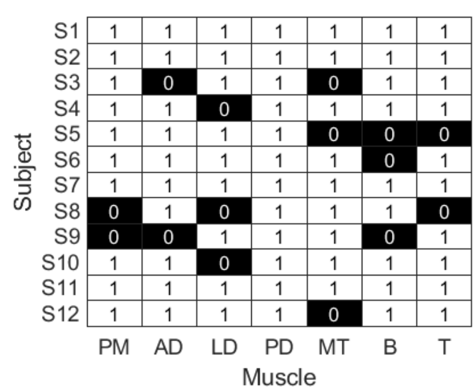

Figure 3: The EFI showing (1) or not showing (0) a significant ($p < 0.05$) monotonically decreasing trend by the Mann-Kendall test.

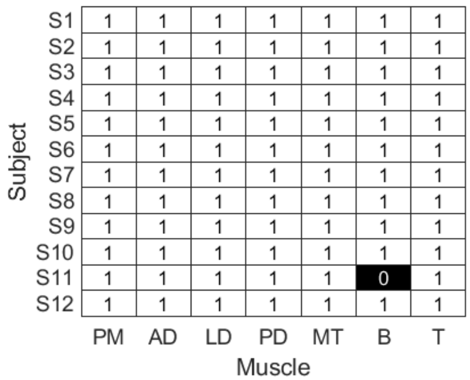

Figure 4: The noise level of the SFI significantly ($p < 0.05$) smaller (1) or not significantly smaller (0) than the relevant EFI.

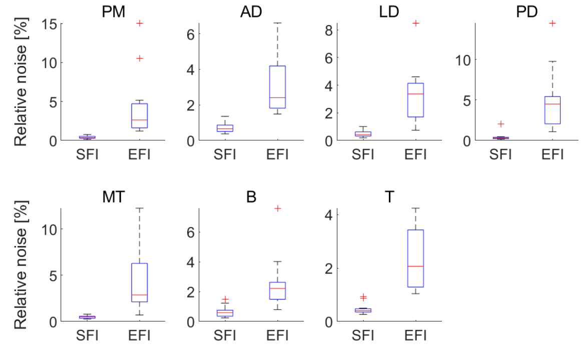

Figure 5: Box and whisker plots illustrating distributions of the relative noise levels across all participants of the SFI and the EFI metrics for each muscle.

Furthermore, as illustrated in Figure 4, statistical tests showed that the SFI had significantly ($p < 0.05$) smaller noise levels in all but one of the studied muscles, compared to the purely EMG-based fatigue indices. This reduction in noise levels is even more evident from Figure 5, which shows the muscle-specific box and whisker plots of the relative noise terms obtained from the SFI and EFI metrics for all participants. There was only one exception (the B muscle of Subject 11) in which case the relative noise associated with the SFI was not significantly smaller than the relative noise associated with the EFI. The corresponding EFIs and SFIs are shown in Figure 6, where one can see that the two indices behave in a relatively similar way, with similar levels of noise. Nevertheless, even in that case, SFIs show lower levels (0.73%) of relative noise compared to the EFIs (0.80%), only with false alarm levels slightly higher than the standard $p = 0.05$ (significance is established only at false alarm rate of $p = 0.1183$). For comparison, Figure 7 shows a more typical case in which SFIs show much lower noise levels compared to the EFIs.

Besides observing the overall stronger monotonicity and reduced noise levels provided by the SFI metric, we also observed some interesting differences in temporal evolutions of SFIs for different participants. Namely, we observed that

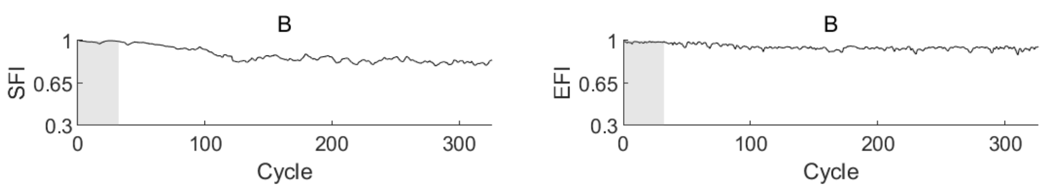

Figure 6: The SFI and EFI of the B muscle of Subject 11, an example when the SFI and EFI both showed monotonically decreasing trend and had similar noise level. The gray patches indicate the portion of data used for training the model and constructing the fresh distribution of model residuals for the SFI or for constructing the fresh distribution of the EMG instantaneous frequency for the EFI.

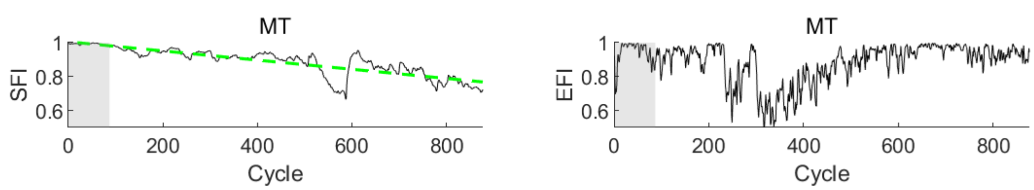

Figure 7: The SFI and EFI metrics of the MT muscle of Subject 3. This is an example in which the SFI has a statistically lower levels of relative noise compared to the EFI indices. Furthermore, unlike EFIs, SFIs for this muscle show a significant ($p < 0.05$) monotonically decreasing trend, as per Mann-Kendall test.

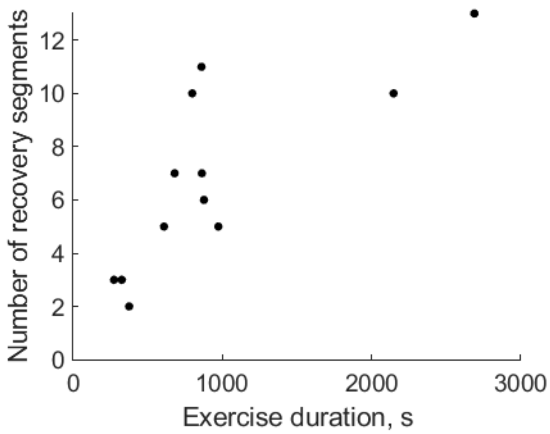

Figure 9: Number of recovery segments versus exercise duration.

exercise durations for various participants varied widely[5], from 274 seconds for the participant who exercised the shortest amount of time, to 2688 seconds for the participant who exercised the longest and who also just happened to be a triathlete. Furthermore, we also observed that in many cases, certain muscles showed slight recoveries of SFIs in later stages of the exercise, as if there was some recovery in the performance of those muscles. Anecdotally, endurance athletes often report the ability to change the way they perform an exercise or a task to rest some muscles and thus endure that task or exercise longer. We wanted to quantitatively evaluate if there was a relation between the time-durations of each participant's exercise and their muscles showing signs of performance recovery in their corresponding SFIs.

To do that, we evenly divided temporal evolutions of each SFI into five segments. If the SFI during one segment showed a statistically significant ($p < 0.05$) monotonically increasing trend as per the Mann-Kendall test, the segment would be identified as a recovery segment. A Pearson correlation coefficient was then computed to assess the relationship between the exercise duration and the total number of recovery segments for each subject. We found there was a strong, statistically significant positive correlation between the two variables, $r = 0.78$, $n = 12$, $p = 0.0028$. The scatterplot in Figure 9 summarizes exercise durations and numbers of recovery segments for each participant, while Figure 8 shows temporal evolutions of muscle-specific SFIs of the shortest and the longest performing participant in the study, with degradation and recovery segments highlighted within the plots. One can clearly see many more recovery segments (13 recovery segments) in the SFI evolutions of the longest performing

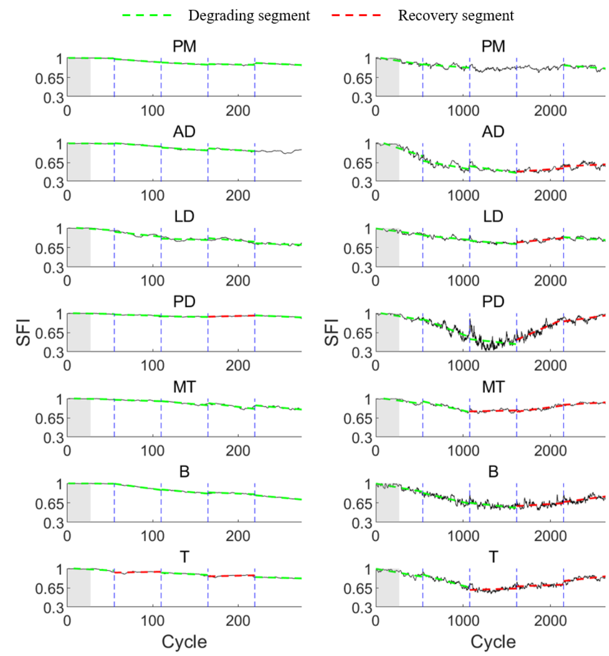

Figure 8: The SFI of the shortest (left) and the longest performing subject (right). Each SFI was divided evenly into five segments. The green dashed line in each segment indicates a significant negative slope of the linear fit to the SFI, while the red dashed line indicates a significant positive slope and was regarded as recovery behavior in the SFI.

participant, compared to what we see with the shortest performing participant (only 3 recovery segments).

5. CONCLUSIONS AND FUTURE WORK

In this study, we proposed a novel system-based approach for monitoring muscle fatigue by merging physics-based and data-driven approaches which enable fusion of EMG signatures with measurements of kinematic and kinetic variables. The method is evaluated using data obtained from a repeated sawing motion experiment involving 12 participants. The proposed system-based fatigue metric consistently reflected the progression of muscle fatigue with stronger monotonicity and reduced noise levels compared to a traditional muscle fatigue indicator based solely in EMG signal analysis. Furthermore, the novel system-based monitoring approach revealed different muscle fatigue progression patterns among different participants in the experiment. Notably, a statistically significant, strong correlation was established between the time each participant was able to perform the exercise until voluntary exhaustion and the number of time segments in the exercise during which

[5] The three shortest performing participant exercised between 274 to 375 seconds, while the two longest performing participants exercised for 2147 and 2688 seconds respectively. The exercise time of the other participants varied between 609 and 973 seconds.

at least some muscles of that participant showed temporary performance recoveries. This observation quantitatively points to the ability of those who exercised longer to temporarily change the way they executed the prescribed motion in order to briefly rest some muscles and thus extend the exercise duration. This is something endurance athletes intuitively understand and report and one should note that the participant who exercised the longest in our study was indeed a triathlete.

Future work may be needed to formally evaluate connections between the newly introduced SFI indices and other, non-intrusively obtained metrics of muscular fatigue, such as Maximal Voluntary Contraction (MVC) (Vøllestad, 1997) or Rate of Perceived Exhaustion (RPE) (Borg, 1990). Even though, unlike SFI measures of muscle fatigue, MVC and RPE metrics cannot be obtained in real-time, during exercise, and are less quantitative in their nature than SFI or EFI indices, they are more prevalent in literature and can be considered as relatively accepted macroscale indicators of muscle fatigue among clinicians and researchers (Debold, 2012). In addition, comparing the system-based and the symptom-based approach may be conducted by monitoring muscle fatigue during less constrained motion, such as running or biking at different speeds. This could further demonstrate the benefits of the system-based monitoring paradigm because of the higher variability in both the system inputs (EMG, kinematics) and outputs (muscle forces) during such motions. Furthermore, system-based fatigue metrics analyzed in this study occasionally indicated brief, localized muscle performance recoveries during exercise and occurrence of those performance recovery segments was shown to be correlated with exercise durations. Future research involving system-based performance metrics, such as the one introduced in this paper, should further investigate if and how muscle fatigue progression patterns of highly trained endurance athletes determine their ultimate performance, or how those patterns compare against what we see in the general population. Finally, enhanced ability to accurately track muscle fatigue has significance in eventually guiding the prescription of customized training and rehabilitation plans, as well as design of precision-customized orthotic and assistive devices.

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