System-based Monitoring of Muscular Fatigue in Lower-Extremity Movement

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Abstract

Physical fatigue accounts for many injuries in the workplace, sports arena, or battlefield. The traditional approaches to monitor fatigue rely on detecting and measuring shifts in the person's muscular surface electromyography (sEMG) signals. However, assessing neuromuscular fatigue based purely on sEMG signals fails to account for the changing muscle dynamics during long dynamic physical tasks. To combat this dilemma, a system-based methodology has been recently developed and applied to several upper-extremity tasks. In this paper, we validate the efficacy of this novel methodology on the lower extremities during a dynamic activity. Specifically, the system-based monitoring methodology was applied to a cycling endurance task. It was statistically demonstrated that the system-based methodology resulted in a more-sensitive and less noisy metric, in comparison with an EMG-based methodology. The efficacy of the methodology was further illustrated by analyzing the inter-segmental recovering and fatiguing trends, which aligned with each muscle's expected inter-muscle synergistic relationship.

1. Introduction

There are two forms of physical fatigue: central and peripheral. Central fatigue is defined as a decrease in the voluntary activation of the muscle. Peripheral fatigue is seen as a decrease in the contractile strength of the muscle fibres and any change in the underlying dynamics of the muscle (Boyas & Guével, 2011). Physical fatigue can be seen in the various physical tasks undertaken by workers (Antwi-Afari, Li, Edwards, Pärn, Seo & Wong, 2017), athletes, and soldiers (Gefen, 2002). For example, those in the construction industry experience the damaging effects of unmitigated fatigue (both physical and/or mental) (U.S. BLS, 2016).

A common method for assessing peripheral fatigue involves analyzing the surface electromyographic (or sEMG) signals of the physiologically relevant muscles during a given physical task. Fatigue is commonly identified and tracked via a downward shift in the instantaneous mean frequency, and/or an upward shift in the instantaneous amplitude of the sEMG signal (Vøllestad, 1997). A limitation of this method is that it only considers the inputs (sEMG) into the muscle, ignoring the ever-changing muscle dynamics during a physical task. This situation is analogous to analyzing the condition of an automotive engine based solely on the engine's temperature and vibration levels, while ignoring the position of the gas pedal, engine's previous mileage, or current road conditions. The limitation of this method is exacerbated during an endurance task, such as submaximal cycling. As time progresses, the participant's muscles will no longer respond in the same way for a variety of reasons (e.g., less oxygenated blood, muscle activation history, body temperature, etc.) (Enoka & Duchateau, 2008).

Fortunately, with the recent advances in cheaper, more effective biosensors in everyday life and the improvement of data-driven models in machine learning algorithms, new opportunities have emerged to model and evaluate a human's condition and performance, from the workplace to the physical therapy room. Patel, Tiwari, Pandey, and Nikam (2020) utilized a computer vision-based method to assess driver fatigue and drowsiness. Dindorf, Bartaguiz, Dully, Sprenger, Becker, Fröhlich and Ludwig (2023), which measured in real-time the muscle's oxygen saturation level via a near-infrared biosensor to assess the fatigue of climbers over a period of consecutive dead hangs. Zhang, Lockhart, and Soangra (2013) utilized support vector machines to classify the participant's gait cycle as "normal" or fatigued. Finally, Ou, Gates, Johnson, and Djurdjanovic (2022) captured the ever-changing muscle dynamics during a cyclic upper extremity task by building a Growing Structure

Multiple Model System (GSMMS) during the participants' "fresh" state and monitoring the participants' fatigue via the model's predicted muscle force error. Their findings showed a significantly less noisy fatigue metric relative to traditional sEMG-based methods allowing for analysis of individual muscle recovery and fatigue. It should be noted that this method does require the external forces of the participant be measured for muscle force estimation. While this requirement does increase the data acquisition complexity, the methodology has shown a less-noisy fatigue metric and the advancement and proliferation of smart force sensors in health and industry have made this requirement much more achievable.

However, this method has not been applied to nor verified on lower extremities during dynamic activities. Additionally, the recovering/fatiguing trends identified via the system-based fatigue monitoring methodology requires further investigation in their inter-muscle relationships.

In this paper, we apply a data-driven dynamic model to characterize the peripheral fatigue of the lower extremities in a cycling endurance task. This paper furthers the realm of applications for a system-based fatigue monitoring methodology to include movements of lower extremities, which has not been addressed in the literature thus far. Additionally, patterns of fatigue and recovery of individual muscles are analyzed to further validate the effectiveness of this methodology by assessing muscle pairs with similar biomechanical function. In Section 2, we review constituent components that embody this system-based methodology. In Section 3, we describe the pilot cycling trail and experimental setup. In Section 4, we describe and analyze the findings of the trial. In Section 5, we dive into a discussion of the results and planned future work.

2. METHODS

The system-based monitoring paradigm has seen numerous successful applications in the recent years, including monitoring of automotive engine systems (Cholette & Djurdjanovic, 2012), semiconductor manufacturing tools (Bleakie & Djurdjanovic, 2016), and human muscle performance (Musselman, Gates, & Djurdjanovic, 2017 and Madden, Djurdjanovic, & Deshpande, 2021). This methodology's success can be attributed to its ability to capture not only the anomalies in the input and output signals emitted by a system, but also any anomalous relationships between the inputs and outputs. By modeling the dynamic relationship between the entity's inputs and outputs, one can analyze how this relationship changes over time, as well as adapt said dynamic model to ensure accurate prediction capabilities, as seen in Bleakie and Djurdjanovic (2016).

In order to best characterize the complexity of sEMG signals, we applied Cohen's class of time-frequency distributions (Cohen, 1995) to adequately represent patterns of energy fluctuations in those signals in both the time- and frequency-domain. In particular, the binomial time-frequency kernel was utilized because of its computational efficiency, which allows for real-time signal processing, while at the same time, binomial kernels minimize non-intuitive cross terms within the time-frequency representation of the signal (Choi & Williams, 1989)

Using the binomial kernel, we were able to extract temporal evolutions of the instantaneous means, intensities, and entropies from each muscle's sEMG signal over the length of the exercise. Time-series of these features were then used as inputs for both fatigue monitoring methodologies. Figure X shows the raw sEMG signal and the time-frequency extracted features from the tibialis anterior muscle of the right leg during the first 30 seconds of the trial.

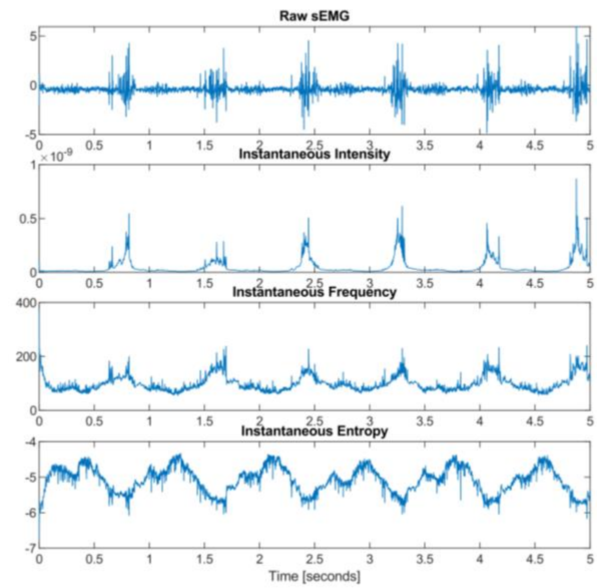

Figure 1. Raw sEMG and time-frequency extracted features for tibialis anterior during the first 5 seconds of the trial.

In order to apply a system-based monitoring paradigm, one must provide time-series of input and output variables for each muscle that is being monitored. Nevertheless, muscle forces, which can be seen as outputs of a muscle as a dynamic system at any given time, cannot be measured directly, especially during a complex dynamic task, such as cycling. Following a simplified Hill-type model (Hill, 1938), forces generated by a muscle depend on multiple variables: muscle pennation angle, muscle length, muscle velocity, and previous muscle activations. Furthermore, the relationship between electrical muscle activations and force generation is highly nonlinear (Millard, Uchida, Seth & Delp, 2013). Hence, in order to build and track an adequate data-driven model of each muscle's dynamics, it is necessary to extract the aforementioned muscle parameters, along with estimated muscle forces and feed these features into a nonlinear dynamics model that could predict the forces generated by that muscle within a reasonable accuracy.

Rather than directly measuring muscle forces, which is unfeasible in our dynamic use case, this paper follows Ou et. al (2022) and pursues indirect estimation of muscle generated forces using first-principle physics and available external measurements. For this reason, OpenSim commercial software was employed (Delp, Anderson, Arnold, Loan, Habib, John, Guendelman & Thelen, 2007). OpenSim is a biomechanical simulation software widely used in the kinesiology, sports science, and medical fields. Due to its utilization and validation in a wide array of applications fields, OpenSim 4.3 was selected as the framework for estimating muscle lengths, velocities and generated forces from the available EMG measurements, movement trajectories and external forces. The flowchart in Figure 1 illustrates how OpenSim was used to estimate the relevant variables.

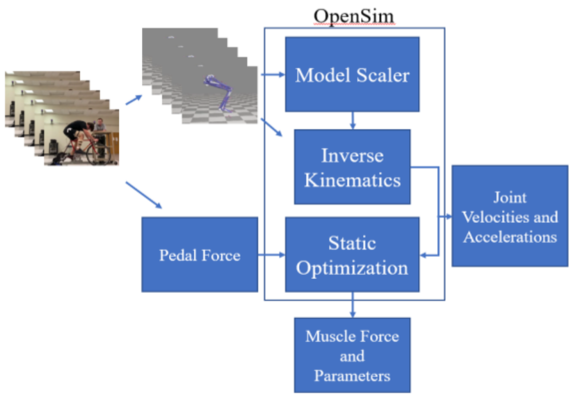

Figure 2. Flowchart showing the conversion from raw data to biomechanical values using OpenSim.First, reflective markers are placed on the participant to estimate the participant's body geometries and track body motions throughout the exercise, while the external forces applied to the participant during the exercise are collected simultaneously. Before the beginning of the trial, the participant was asked to sit at rest on the bike. These motion capture frames were used to scale a generic OpenSim model to fit the anthropometric properties to the participant. In this work, a 3-DOF single-legged musculoskeletal model with 8 Hill-type musculotendon actuators was employed with the contact between the participant and bicycle seat modeled as a pin joint at the pelvis. Then, the scaled model is fit to the resulting dynamic motion capture frames resulting in the model's joint position, velocity and acceleration. Finally, following Ou et al. (2022) static optimization utilized the external forces on the model (e.g., pedal forces) and the model's motion to solve for the generated muscle forces and muscle parameters for each instant in time.

With the sEMG features from time-frequency analysis and the muscle parameters and forces from OpenSim, we have the inputs and outputs necessary for the model. Following Ou et al. (2022), a Growing Structure Multiple Model System (GSMMS) was utilized to model the relations between inputs and outputs of each muscle. These divide-and-conquer type models have local model tractability and interpretability, while at the same time being capable of modeling the well-documented nonlinearities in muscle dynamics (Millard et al., 2013) to within an arbitrary accuracy. Furthermore, any anomalous, or previously never seen inputs to the model, can easily be identified, enabling model growth and adaptation to this newly observed behavior, or alarming the user of uncertain, or untrustworthy, predictions. In summary, GSMMS models are sufficiently complex, while being interpretable and adaptable for the given use case. For more details regarding the GSMMS models, please refer to Liu, Djurdjanovic, Marko, and Ni, 2009 and/or Cholette Djurdjanovic, 2012.

With the time-series of inputs and outputs of the data-driven model, we can train and track the dynamic models of each muscle based on the data emitted during one's exercise. Training of each muscle model was done using data observed in the initial stages of the exercise – when the muscles were least fatigued. During the training period, distributions of errors between the muscle force predictions of the data-driven dynamic model and the participant's muscle forces estimated via OpenSim are generated and characterized using Gaussian Mixture Models (GMMs).

With the training error distribution characterized, the evaluation period began, and the data-driven dynamic model was fed the participant's subsequent inputs, based on which it predicted the participant's generated muscle forces. The prediction error distributions for each muscle were updated iteratively, using the aforementioned Gaussian Mixture Model framework.

The extent to which a given muscle of the participant is fatigued was assessed by evaluating the overlaps between the current (most recently observed) distribution of model prediction errors, and the one observed during training for the relevant data-drive muscle model. The overlaps, or similarities between the two distributions were evaluated at each time step using Matusita's coefficient (1967). If the participant is fresh, or unfatigued, the relevant distributions will match well, and the similarity index will be close to one. As the participant becomes more fatigued, the muscle dynamics change, thus altering the distribution of predicted muscle force errors and causing the similarity index to decrease towards zero. Following Ou et al. (2022), this metric will be referred to as the System-based Freshness Index (SFI).

To fairly compare the SFI metric with purely signal-based fatigue metrics, the same distribution similarity concept was applied to the instantaneous sEMG frequencies of the participant. This purely signal based metric is a well-established measure of muscle fatigue (Arendt-Nielsen & Mills, 1985; Georgakis, Stergioulas and Giakas, 2003; McDonald, Mulla, and Keir, 2019). Namely, distributions of the instantaneous sEMG frequencies of the participant are generated for each muscle during the training period. As the exercise progressed, these distributions described using the GMM framework are updated and compared with those observed during the training process.

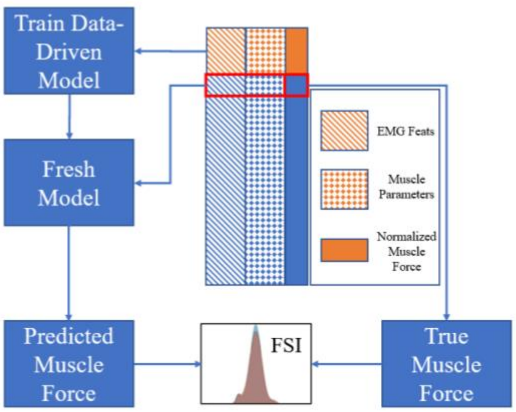

Figure 3. Diagram showing the system-based fatigue monitoring (SFI) methodology.

Following Ou et al. (2022), the resulting fatigue metrics will be referred to as the EMG-based Freshness Index (EFI). A flowchart of the System-based Freshness Index is shown in Figure 2.

3. EXPERIMENTAL SETUP

For this pilot trial, one participant elected to perform the cycling task until complete exhaustion (defined by the inability to maintain power output). According to Neptune and Hull (1998), the major muscles that contribute to cycling are the tibialis anterior, vastus medialis, semitendinosus, soleus, gastrocnemius, biceps femoris, gluteus maximus, and rectus femoris as shown in Figure 3 and listed in Table 1.

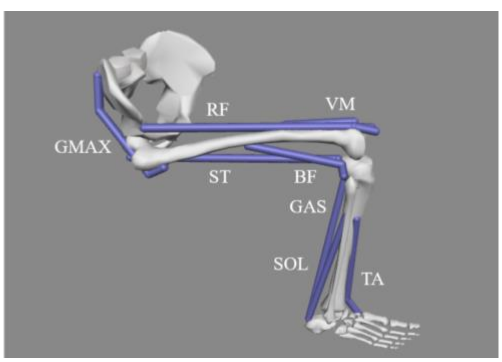

Figure 4. Illustration of the eight muscles monitored during the cycling trial. Graphic obtained using OpenSim (Delp et al. 2007)

Table 1. Muscles monitored during the cycling trial.

Abbreviation	Muscle
TA	Tibialis Anterior
SOL	Soleus
GAS	Gastrocnemius
VM	Vastus Medialis
RF	Rectus Femoris
GMAX	Gluteus Maximus
BF	Biceps Femoris
ST	Semitendinosus

These eight muscles of the right leg were monitored via Delsys bilateral electrodes at a sampling rate of 2000 Hz. 21 reflective markers were placed from the hip of the participant to the pedals of the bike according to the recommendations of OpenSim (Delp et al., 2007) to ensure the accuracy of the simulation. A 10-camera motion capture system recorded the participant's motion at a sampling rate of 100 Hz (Vicon, Oxford, UK). The reflective marker trajectories were low-pass filtered at a frequency of 6 Hz to ensure stable differentiation during the numerical calculation of the participant's velocity and acceleration as recommended by Delp et al. (2007). The pedal forces in the normal and tangential planes were recorded at 2000 Hz using a pedal dynamometer (Newmiller, Hull, & Zajac, 1988).

Due to the memory limitations of the motion capture system, we were not able to collect motion capture data for a period longer than 30 seconds. Thus, all plots will have discontinuities between each segment of the data. To avoid confusion, the periods without data are replaced with thick black vertical bars in between recorded periods for all plots.

Finally, the participant's resistance was calibrated prior to the beginning of the trial by brief periods of various resistances. To ensure complete exhaustion at a cycling rate of 75 RPM, a resistance of 250W was selected for this participant's trial. Throughout the trial, the participant was shown the current pedaling rate and instructed to maintain a rate of 75 RPM for as long as possible.

The GSMMS model was trained on the participant's "fresh" state, so the first 5 seconds of the trail were utilized. The remainder of the trial (205 seconds) were utilized as the test dataset. The error distribution of the "fresh" state/training dataset were compared with the error distribution of the current state/test dataset utilizing Matusita's coefficient (1967) as in Ou et al. (2022).

4. RESULTS

The participant cycled for a period of 6.5 (six and a half) minutes before they were completely fatigued. This resulted in seven full periods of data collection of the participant's sEMG signal and reflective markers.

4.1. Signal-to-Noise Ratio

Following Ou et al. (2022), we compare the relative noise of each fatigue metric over the duration of the trial. Figure 4 displays the relative noise for each index.

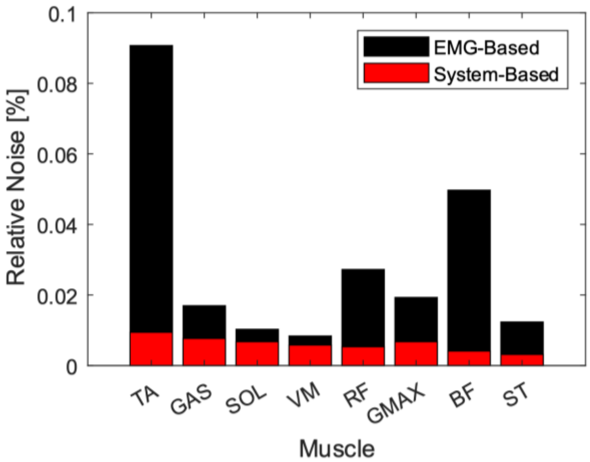

Figure 5. Relative noise of the sEMG-based freshness index (EFI) and system-based freshness index (SFI) metrics during the entire trial for all eight muscles.

As seen in Figure 4, the system-based freshness index (SFI) has a lower signal-to-noise ratio for all eight muscles during the entire trial. Furthermore, in Figure 5, one can that the SFI was significantly less noisy than the EMG-based freshness index (EFI), as evaluated using a one-sided t-test ($p < 0.05$) of the EFI and SFI relative noise distributions over the entire trial. This finding agrees with what was found in Ou et al. (2022) in their upper-extremity task, further validating the usefulness of this fatigue metric.

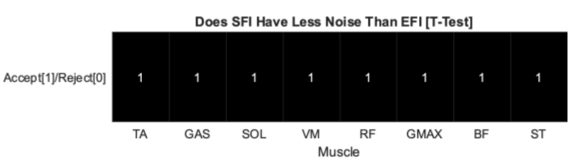

Figure 6. Results of T-test indicating whether the system-based freshness index (SFI) was less noisy than the sEMG-based freshness index (EFI), with statistical significance ($p<0.05$).

4.2. Participant Fatiguing/Recovering Trends

4.2.1. All Trial

Previous studies have determined that all eight muscles evaluated in this paper are important contributors to cycling (Neptune & Hull 1998), and the participant biked until complete exhaustion. Hence, a decreasing trend should be expected in each muscle's fatigue metric across the entire trial (EFI/SFI). To confirm, we applied a Mann-Kendall statistical trend test (Mann, 1945; Kendall, 1975) to both the EFI and SFI metrics. The relevant results are shown in Figure 6, with metrics that have a statistically decreasing first-order trend being denoted in red.

For the EFI, all but the gastrocnemius (GAS) and soleus (SOL) muscle show a statistically significant decreasing trend. However, the SFI shows a statistically significant decreasing trend across all eight muscles. The fact that the EFI failed to show trial-long fatigue in both plantar flexor muscles (GAS and SOL) indicate potential lack of sensitivity when it comes to monitoring based on only the sEMG signals from the muscle. This can be explained by the fact that, while the central nervous system may send almost the same electrical stimuli to a muscle (as seen in the GAS muscle in segment 4), factors such as blood-oxygen levels, duration of activity, and body temperature (Enoka & Duchateau, 2008) reduce the muscle's ability to produce the same output force. Consequently, given the same inputs in segment 1 and 4, the data-driven model will predict the same output force. Yet, the error distribution in segment 4 will have been different than in segment 1 due to the aforementioned factors that occur during fatigue which are not captured by the sEMG signal. On the other hand, since the SFI was built on the relationship between the muscle inputs (sEMG) and muscle outputs (force), the SFI was more sensitive and was able to capture the peripheral fatigue of each muscle.

4.2.2. Intersegment Trends

During exhaustive cyclic tasks like cycling, the human body can exploit its muscle redundancy to stave off fatigue by recruiting functionally similar muscles, while resting those muscles that were previously enacted and became fatigued. In other words, participants can rest one group of muscles, while working a different group of muscles and alternate these groups until one or both groups of muscles are exhausted. Such synergies (d'Avella, Saltiel, & Bizzi, 2003), or motor modules (Clark, Ting, Zajac, Neptune & Kautz, 2010), have been defined as groups of muscles that coactivate during a certain motor task are well known. For example, to increase the torsional stiffness of the ankle joint, the soleus/gastrocnemius and tibialis anterior are coactivated. As these muscle pairs are enacted in unison, they will be referred to as synergistic muscle pairs. We seek to analyze the muscle synergies of the muscles during this cycling trail for two reasons: 1) to further validate the SFI metric and 2) to evaluate other possible uses for the SFI metric.

To demonstrate this, we split the SFI metric into its respective segments and performed the same Mann-Kendall trend test to identify if the muscle was fatiguing (decreasing SFI) or recovering (increasing SFI). In Figure 7, the segmental trends are shown with fatiguing trends in red and recovering trends in green. Let us first note that there are two sets muscle pairs that have similar biomechanical functions in this exercise: the soleus (SOL) and gastrocnemius (GAS) muscles, and the bicep femoris (BF) and semitendinosus (ST) muscles.

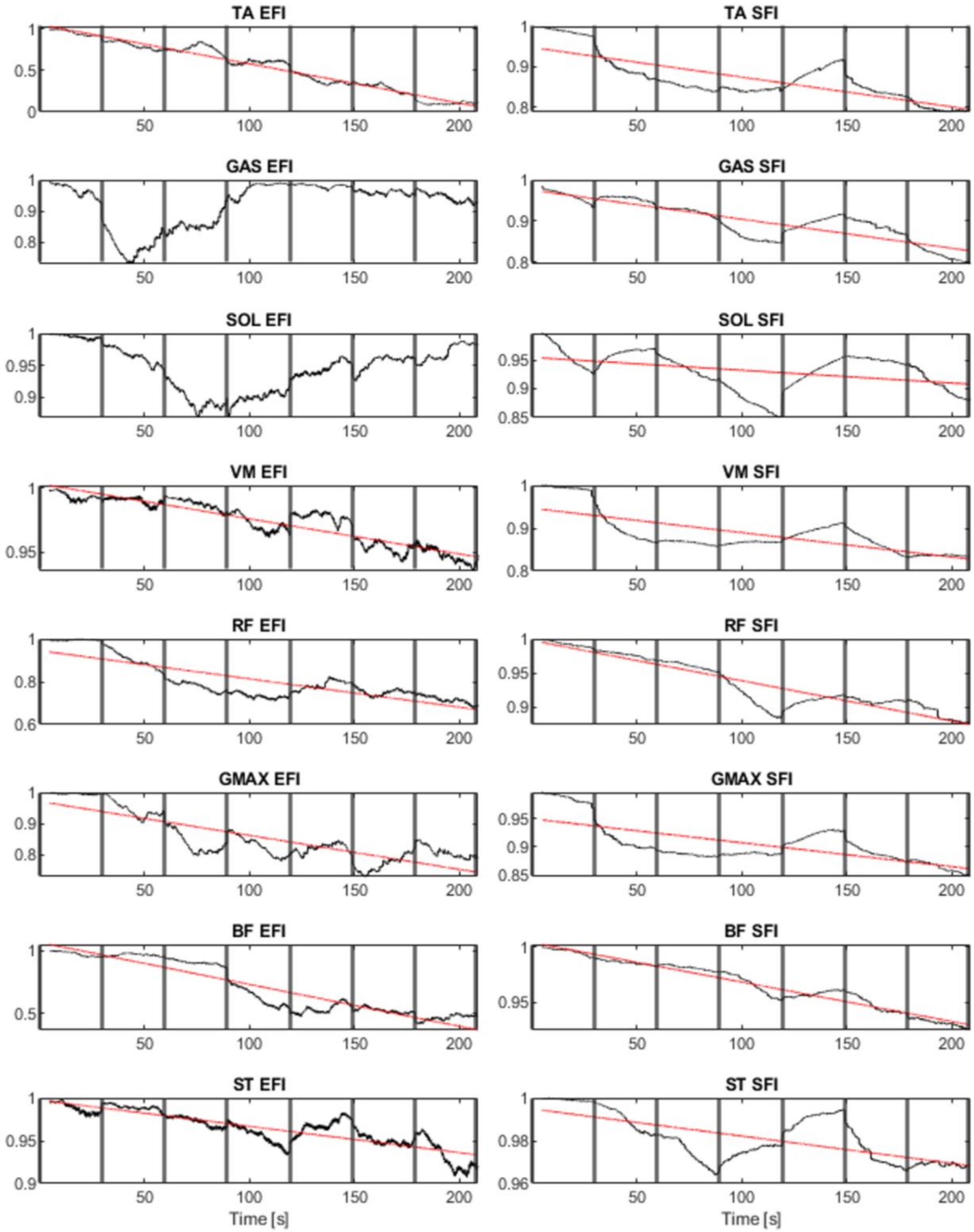

Figure 7. Monotonically decreasing (red/fatigue) trends of the sEMG-based freshness index (EFI) and system-based freshness index (SFI) across the entire trial.

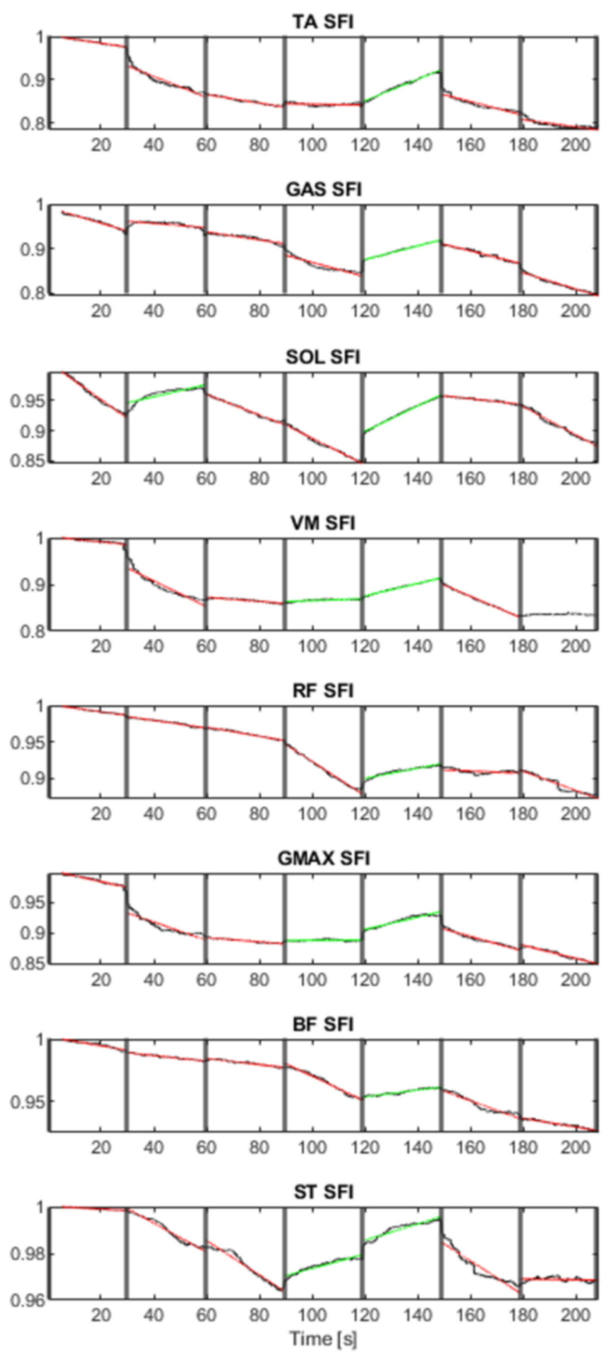

Figure 8. Monotonically decreasing (red/fatigue) and increasing (green/recovery) trends of the system-based freshness index (SFI) across the entire trial.

The bicep femoris and semitendinosus muscles are enacted during knee flexion, and thus one muscle can compensate for its partner and vice versa. This relationship can be seen in segment four when the semitendinosus (ST) muscle recovers while the biceps femoris (BF) muscle continues to fatigue with a steeper slope than the previous segment. The same relationship can be seen in our other functionally similar muscle pair. In segment two, the gastrocnemius (GAS) muscle fatigues while the soleus (SOL) muscle recovers.

An interesting phenomenon occurred in segment five. During that period, all eight muscles demonstrated a recovering period in FSI, despite almost all other segments demonstrating a fatiguing trend. If one's attention is directed to the EFI of segment five, five of the eight muscles showed a recovering period in the EMG inputs, while the remaining three showed a fatiguing period. A possible explanation for this period would be a sharp increase in the recruitment of additional motor units and/or fast twitch muscle fibers. This would help explain the relative return of the sEMG signal and the steep recovery of the generated muscle force. Namely, it has been demonstrated that slow-twitch fibers are recruited first, while fast-twitch muscles fibers are recruited later and only when necessary (Petrofsky, Phillips, Sawka, Hanpeter, Lind, & Stafford, 1981). Potentially, the inability of the user's slow-twitch muscle fibers to maintain the required force just prior to segment 5 necessitated the recruitment of fast-twitch muscle fibers in the near-completely fatigued muscle. This was, obviously, followed by a consistent decrease in performance for all muscles in segments 6 and 7 until complete exhaustion.

5. Conclusions and Future Work

This paper was the first one to apply a system-based fatigue monitoring paradigm to the lower extremities during a dynamic endurance task and validate the efficacy of the paradigm utilizing muscle synergies and the SFI. It was observed that the system-based approach to monitoring of muscle performance has a lower signal-to-noise ratio than the traditional sEMG-based approach. Additionally, unlike the purely signal-based approach, the novel system-based approach consistently detected fatigue in all muscles analyzed during this trial. Finally, the intersegmental trends seen using the system-based approach agree with each muscle's biomechanical function and their synergies with other muscles. These findings further validate the effectiveness of this methodology to assess fatigue, while extending its applicability to the lower extremities and identifying muscle synergies.

While these results reinforce the effectiveness of the system-based methodology relative to the traditional sEMG-based methodology, one should seek to use other fatigue assessment methodologies for further comparison and validation. In particular, the pulmonary O_2 intake ($\dot{V}O_2$) and blood glucose level could help isolate certain factors related to increased fatigue. Jones, Grassi, Christensen, Krustrup, Bangsbo and Poole (2011) found that the slow component of $\dot{V}O_2$ to be closely related to muscle fatigue, while Nybo (2003) found that available glucose in the bloodstream correlated to the amount of neural drive ("central fatigue"). Additionally, San-Millán, Hill, and Calleja-González (2020) utilized sonomyography to assess pre- and post-game fatigue of individual muscles via estimation of glycogen content. Using these metrics as benchmarks of fatigue and an increased number of participants in the trial, we can further test the validity of the system-based framework.

ACKNOWLEDGEMENT

The authors would like to thank the Cyber Security Manufacturing Innovation Institute (CyManII) for funding this work.

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