Monitoring Human Neuromuscular System Performance during Space Suit Glove Use: A Pilot Study

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Abstract—**This paper presents the application of a system-based modeling technique for performance monitoring of the human neuromusculoskeletal (NMS) system during space suit glove use. Autoregressive moving average models with exogenous inputs (ARMAX) were used to characterize the dynamics of the NMS system and its changes over time during two types of tasks: isometric grasping and repetitive opening and closing of the hand. Features extracted from the joint time-frequency distributions of surface electromyography (sEMG) signals collected from flexor and extensor muscles of the forearm were used as model inputs, whereas biomechanical data, either grip force or fingertip travel, were utilized as outputs. A quantitative metric comparing one-step ahead prediction errors of the model over time, called the Freshness Similarity Index (FSI), was employed to monitor and track divergence from normal NMS system behavior. The observed trends in FSI offered a succinct representation of how an individual's performance degraded and was used to illustrate the manifestation and rate of fatigue. These methods were demonstrated on pilot data collected from a single subject. For each task performed, the subject displayed statistically significant increasing trends in the dissimilarity between the NMS system at a rested state and subsequent periods throughout the test. The trends exhibited consistency across multiple days of testing, the resolving power to distinguish differences in prescribed force exertion and glove conditions, and the ability to identify the accumulation of residual fatigue. The presented work, which characterizes changes in the NMS system, demonstrates the potential to monitor the physiological status of individuals while wearing a space suit. Tracking NMS performance over time is important for ensuring space mission safety and success. As such, these methods can be implemented for assessing human health, recognizing the onset of abnormal performance, and evaluating fitness-for-duty during manned space exploration missions.**

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1. INTRODUCTION

Current Extravehicular Activity (EVA) space suits place an encumbrance on an astronaut's ability to move naturally. As a result, the space program has been plagued by overuse and repetitive injuries in the hands and upper-extremities of astronauts [1]. Specifically, the Phase VI EVA glove, which contains state-of-the-art technology, has a multi-layered design that considerably reduces finger mobility and hand grip strength [2], [3], [4]. These decrements are further exacerbated by the presence of a 4.3 psi space suit pressure differential, which is a principal reason why hand and forearm fatigue is amongst the top three most common types of injuries enduredduring EVA missions [5], [1], [4]. Furthermore, spacesuit glove-induced fatigue has been shown to reduce productivity and task efficiency during during EVA missions [4]. Fatigue, in general, is also known to impair movement accuracy [6], which can be especially dangerous during long duration EVA tasks. As plans for planetary and lunar explorations become more imminent, the future of space exploration relies upon the ability of individuals to perform hand intensive tasks, such as shuttle repair and habitat construction, while outside the confines of an environmentally controlled space vehicle. For this reason, tracking an individuals health status during EVA is important for ensuring space mission safety and success.

The current, practice for evaluating muscle fatigue involves symptomatic methods that quantify and monitor trends in either the input(s) or the output(s) of human movement over time. For instance, measuring mechanical failure [4], [7] based on when a subject becomes unable to sustain a desired force, is a common output-based symptomatic monitoring approach. A prevalent input-based approach in the literature, although not extensively explored in the space suit community, is measuring physiological, or metabolic, fatigue of muscles via surface electromyography (sEMG) [8], [4].

However, studies that have performed quantitative analyses on spacesuit glove-induced fatigue using sEMG have limitations. This research avenue has relied upon conventional spectral analysis preventing the direct measurement of fatigue during dynamic contractions [7], [9], developed time-dependent amplitude-based metrics [10] that should be used in conjunction with spectral parameters to be considered indicators of fatigue [11], and recruited only a small subset of the many extrinsic muscles that control hand movement. Muscle-level fatigue monitoring using sEMG is attractive because it offers independent analysis of different muscles, however, it increases the dimensionality of the fatigue monitoring process as the number of muscles grows. In this way, it is not ideal for delineating a compact representation of overall subject fatigue [9].

A major drawback of symptomatic monitoring methods is the underlying assumption that the system inputs are stationary, which follows the logic that aberrant behavior in the output

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or input is indicative of an deviant system. This presumption is inherently untrue for physiological systems. System-based monitoring avoids this deficiency because it takes into consideration both inputs and outputs to the system and constructs a dynamic relationship between them. By monitoring the input-output dynamics, model-based methods can track the performance of the system without requiring the input to be stationarity. This type of paradigm allows the discernment between changes in system behavior due to alterations in dynamics or unusual inputs.

The human nervous system provides information about how the NMS system controls limb movement. Signals from the brain and spinal cord are relayed to the muscle fibers where action potentials engage contractile proteins in the fibers to generate forces needed for movement [12]. The electrical activity of the muscle fibers during the contraction can be intercepted by sEMG sensors placed on the skin. In this way, sEMG signals can be considered indirect inputs of the NMS system. Furthermore, muscle force generation induces joint torques causing the human limbs to move. Kinematic and kinetic variables, measured via dynamometers, position sensors, etc., can be used to quantify output forces and joint angles of the human limb. Thus, with muscular inputs and biomechanical outputs, a system-based monitoring paradigm can characterize and track changes in NMS dynamics.

Work has been done using system-based modeling to estimate human joint motion from sEMG for controlling robotic arms [13] and monitoring electrically stimulated muscle activity to predict human joint torques [14] and muscle forces [15]. Only recently has interest emerged in system-based monitoring of the human NMS to track performance degradation of voluntary movement, however. Musselman et al. used instantaneous intensity and frequency features of sEMG signals as model inputs and joint kinematics as outputs to a linear autoregressive model with exogenous inputs (ARX) [16] to describe system dynamics during a planar repetitive sawing motion until exhaustion. Degradation of normal behavior was effectively quantified by the amount of overlap between the distributions of one-step ahead prediction errors of the subjects least-fatigued state and current state. This work was extended by the same group who recruited higher order statistics for sEMG inputs and autoregressive moving average models with exogenous inputs (ARMAX) [17] to quantify both fatigue and recovery during pilot studies. Furthermore, these methods were expanded to use a nonlinear dynamic models, to accommodate poor model performance when muscles behave differently (most likely due to synergistic compensation), by employing divide and conquer type models [18]. Despite the advancements in model-based monitoring of the NMS, the application of these methods for monitoring and assessing human health during functional EVA tasks while wearing a space suit garment have yet to be shown.

Due to the high rates of overuse and repetitive injuries during EVA missions and antiquated means of quantifying fatigue, there arises an inherent need for a more advanced approach for not only quantifying space suit-induced fatigue, but also monitoring and assessing the health of an individual during a space mission. This paper seeks to address the demand by demonstrating the efficacy of a system-based monitoring technique in quantifying and tracking fatigue-induced changes in the NMS system of a subject performing common EVA-like tasks while wearing a space suit glove.

2. Pilot Study

Subjects

A single NASA civil servant, whose hand closely fit the NF-sized Phase VI Extravehicular Activity (EVA) Space Suit glove by ILC Dover, Inc, participated in the pilot study. The subject was right-handed and asymptomatic of musculoskeletal disorders affecting his distal upper extremity, as assessed by the Modified Nordic Questionnaire [19]. The subject provided institutionally-approved written informed consent prior to his participation in this study, which took place at NASA Johnson Space Center (JSC) in Houston, TX.

Equipment

The space suit glove used during the experiments was a Phase VI EVA glove that had been modified with robotic grasp capabilities. A detailed description of this device, called the Space Suit RoboGlove (SSRG) (1), can be found in [20], however, a brief explanation of the relevant features of the device will be provided here for completeness. The SSRG works to combat the thickness and the 4.3 psi pressure differential of the space suit by aiding astronauts in closing their hands. The SSRG has tendons that attach to the distal segments of the index, middle, ring, and pinky fingers and connect to linear actuators located around the forearm. Two different types of sensors contribute to different control modes that trigger the actuators to engage the robotic assistance. The first type, called force sensitive resistors (FSRs), monitor interaction forces between the fingers and an object making them particularly beneficial for a task that requires maintaining a constant hand grasp. The second type, called string potentiometers, aid in the opening and closing of the fingers during dynamic, repetitive movement by enabling a control mode that is similar to a power steering mechanism in modern day vehicles [20].

For this pilot study, only the string potentiometer-based control mode was active; the FSR sensors remained turned off. Although not strictly designed to aid in isometric grasping tasks, this control mode is believed to assist slightly in maintaining grip force output was well. Throughout the course of the experiments, the SSRG would be operated both while it was unpowered (i.e. in a passive state where it was not providing robotic assistance, but recording data), and powered (i.e. in an active state where it was providing finger flexion assistance, albeit minimal due to the inactive FSRs). Furthermore, scheduling constraints prevented the SSRG from being pressurized to the standard 4.3 psi space suit pressure differential, for this pilot study. For this paper, the main purpose of operating the SSRG under two different modes, powered and unpowered, was to test the ability of the system-based methods in detecting differences in glove conditions that could affect the rate at which individuals fatigue.

Experimental Protocol

The subject participated in three days of experiments, where days one and three evaluated an isometric grasping task and day two tested a repetitive finger movement task. To obtain a target force that would be used as a reference value for the isometric grasping task, the subject performed two to three maximum voluntary contractions (MVCs). During the MVCs, the subject was wearing the SSRG while squeezing a hand dynamometer as tightly as possible. Each MVC lasted for 5 s with 30 s to one minute of rest in between contractions. The subject was provided with visual force feedback and strong verbal encouragement to maximize his grip force. The

Figure 1. Experimental setup showing the subject wearing the SSRG and squeezing the hand dynamometer during the isometric grasping task.

average of all MVC forces was used to derive the target force value, which was a percentage of this maximum force, to be prescribed during subsequent testing.

The tests for the isometric grasping task on day one were executed while the SSRG was unpowered and powered and either at 20% or 40% of the MVC force value. Specifically, the sequence of tests on day one were as follows: 40% MVC while the SSRG was unpowered, 40% MVC force value while the SSRG was powered, 20% MVC while SSRG was unpowered, and 20% MVC while SSRG was powered. On day three, the testing order consisted of: 20% MVC while SSRG was unpowered and 20% MVC while the device was powered. The 40% MVC grasping tests were performed for a duration of two minutes while the 20% MVC tests were executed for a period of four minutes. During each test, the subject was provided with real-time visual feedback from the hand dynamometer to aid in maintaining a constant force output. Subjects were given at least 10 to 20 minutes of rest between each test, though this varied, and at least 24 hours of rest in between daily sessions.

The tests for the repetitive movement task were performed on day two in the following order: powered SSRG, unpowered SSRG, then powered SSRG again. For this task, tests were executed on the same day with at least 10 to 15 minutes of rest in between. The subject was prescribed to move in accordance to an audible metronome set to 60 beats per minute, taking one second to open followed by one second to close his hand.

Data Collection

sEMG data was collected using a 16-channel Delsys Trigno Wireless EMG system with Trigno Mini sensors (Delsys Inc., Boston, MA). Seven muscles of the forearm, three extrinsic finger and wrist flexors, three extrinsic finger and wrist extensors, and one intrinsic index finger flexor, were targeted for sEMG monitoring. Specifically, the flexor digitorum superficialis (FDS), flexor carpi radialis (FCR), flexor carpi ulnaris (FCU), extensor digitorum (ED), extensor carpi radialis longus (ECRL), extensor carpi ulnaris (ECU), and first dorsal interosseous (FDI) were recruited. Due to possible indications of artifact in the FDI sEMG signal during a handful of tests, this muscle was discarded from the analysis. To prepare for sEMG electrode placement, the subject's forearm was shaved and skin lightly abraded with a pumice stone then cleansed with a isopropyl alcohol. Electrodes were placed along the longitudinal midline of the muscle, oriented parallel to the long axis of the muscle fibers, and placed between the innervation zone and muscle tendon [21], [22], [23]. A bandage was wrapped around them to secure the electrodes tightly against the muscles and prevent possible dislodging from the skin. After each session, electrode locations were marked on the skin with ink to ensure consistent sensor placement across the three day experimental period. A JAMAR A/D hydraulic hand dynamometer was used to collect grip force data during the MVC and isometric grasping tasks. The length of SSRG tendon travel, quantified by the SSRG string potentiometer sensor readings for the index finger of the glove, was used as a kinematic variable indicative of human fingertip travel during the repetitive movement task. Data were acquired continually at 1000 Hz using an xPC Target (Mathworks, MATLAB module) running Simulink Real-Time and hosting NI data acquisition (NI DAQ) boards (National Instruments, Inc., Austin, TX.)

Data Preprocessing

Zero-lag, non-causal Butterworth filters were used to process the raw sEMG signals. The signals were bandpass filtered from 20 to 400 Hz, notch filtered at 60 Hz to remove power line interference, high pass filtered with a cutoff frequency of 6 Hz to remove baseline drift, and de-meaned to remove DC offset. Raw force data from the hand dynamometer were low pass filtered with a cutoff frequency of 6 Hz using a 6th-order Butterworth filter and multiplied by the manufacturers calibration constants. The force profiles were analyzed to identify the time at which the subject reached and maintained the target force level for the isometric grasping tests and truncate the signal for analysis. The string potentiometer data were pre-filtered as described in [20].

3. MODELING METHODOLOGY

The modeling methodology presented here tracks the changes in the NMS system by monitoring the dynamic relationship between neuromuscular inputs, obtained from sEMG signals, and kinematic or kinetic outputs, obtained from grip force or fingertip travel measurements. The modeling procedure includes extracting relevant features from the sEMG signals, modeling the biomechanical outputs as a function of the sEMG features, tracking the modeling errors over time to illuminate NMS system degradation.

Feature Extraction for Model Inputs

Amplitude and spectral parameters of the sEMG signal are closely related to the biochemical correlates of muscle fatigue. They reveal indications of neuromuscular fatigue before the occurrence of mechanical failure [8], which transpires when an individual becomes unable to sustain a desired force or limb trajectory. Decreasing trends in the sEMG median frequency [24], a spectral indicator estimated from the power spectral density, is a classical measure for quantifying and observing muscle-level fatigue. The median frequency, however, is typically restricted to isometric constant force contractions due to its requirements for wide-sense stationarity [25], [26] in the signal. Time-frequency distribution-based spectral estimation has shown to overcome the challenges of sEMG non-stationarity and have been proven effective in identifying fatigue during dynamic force contractions [29]. Furthermore, monitoring increases in sEMG root-mean-square (RMS) amplitude, although rarely used as an indicator of muscle fatigue on its own, can be used in conjunction with spectral indicators to give a clearer distinction between fatigue-induced and force-related changes in sEMG [11].

Joint time frequency analysis using Cohen's class of time-frequency distributions (TFD) was performed to represent changes in sEMG signal energy in both the time and frequency domains. The TFD, $C(t, w)$, of a signal, $s(t)$, is calculated by

$$C(t,w) = \frac{1}{4\pi^2} \cdot \iiint_{-\infty}^{+\infty} s^*(u - \frac{1}{2}\tau) s(u + \frac{1}{2}\tau) \phi(\theta, \tau) e^{-j(\theta(t-u)+\tau\omega)} d\tau du d\theta \quad (1)$$

where $s^*(t)$ signifies the complex conjugate of $s(t)$ and $\phi(\theta, \tau)$ denotes the TFD kernal. The binomial kernal [27], which is a signal independent member of the reduced interference distribution family of kernals, was adopted for this analysis due to its desirable mathematical properties. Not only does it have strong time-frequency support, it upholds the time and frequency marginals, provides instantaneous frequency and group delay, suppresses interference of signals in the time-frequency plane, and delivers faster computation of the TFDs compared to signal-dependent kernals [28]. In this way, time-dependent features that reflect instantaneous amplitude and frequency of the sEMG signal could be reliably extracted. For each instance in time t, the instantaneous energy, $< f^0|t >$, instantaneous frequency, $< f^1|t >$, second order moment, $< f^2|t >$ which is related to the variance of the normalized frequency, and instantaneous entropy, $< S|t >$ were calculated as follows,

$$< f^0|t > = \int_{-\infty}^{+\infty} C(t,\omega) d\omega \quad (2)$$

$$< f^1|t > = \int_{-\infty}^{+\infty} \frac{C(t,\omega)}{< f^0|t >} \omega d\omega \quad (3)$$

$$< f^2|t > = \int_{-\infty}^{+\infty} \frac{C(t,\omega)}{< f^0|t >} \omega^2 d\omega \quad (4)$$

$$< S|t > = \int_{-\infty}^{+\infty} \frac{C(t,\omega)}{< f^0|t >} ln(\frac{C(t,\omega)}{< f^0|t >}) d\omega \quad (5)$$

All sEMG features were normalized to range between 0 and 1 before being used in the model. Examples of extracted features from one muscle are shown in Figure 2. Prominent trends in the features occur as fatigue progresses over time. Specifically, the instantaneous energy, ($< f^0|t >$) increases, instantaneous frequency ($< f^1|t >$) decreases, second order moment ($< f^2|t >$) decreases, and instantaneous entropy, ($< S|t >$) increases.

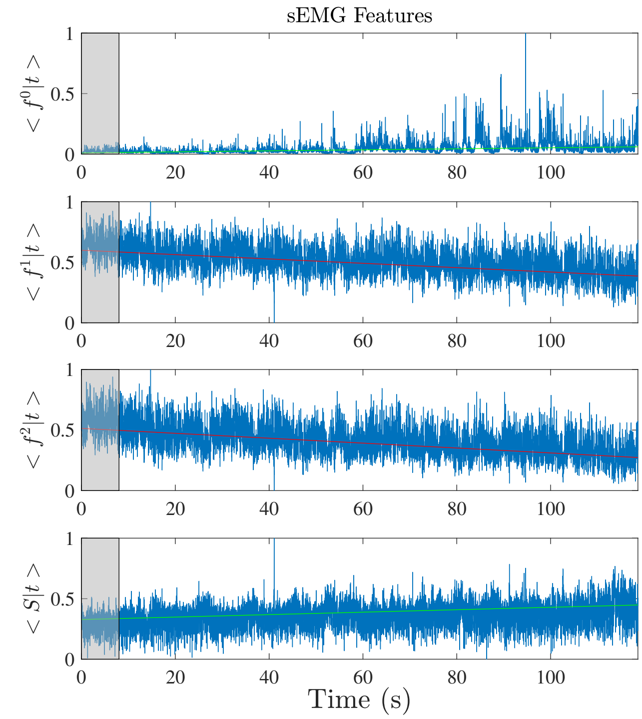

Figure 2. Representative sEMG features from the 40% MVC unpowered isometric grasp test of the flexor digitorum superficialis (FDS) muscle. From top to bottom, the features are instantaneous energy, instantaneous frequency, second order moment, and instantaneous entropy. The gray shaded region indicates the *fresh data* used to generate the reference model. The features themselves are shown in blue. Green lines represent positive and red lines indicate negative statistically significant linear trends (p<0.001).

The instantaneous energy and instantaneous frequency metrics are correlates to the classical spectral and amplitude indicators mentioned above, i.e. median frequency and RMS amplitude. In this way, they are substantiated metrics for assessing muscle fatigue and justifiable inputs to a NMS system model. To verify the system-based methods of NMS performance degradation described in the next section with more conventional methods of monitoring muscle fatigue [6], [12], linear trends in instantaneous energy, $< f^0|t >$, and instantaneous frequency, $< f^1|t >$, were analyzed using a one-sided T test at the 95% confidence interval. As shown in Figure 2, muscle fatigue is indicated by decreases in instantaneous frequency and increases in instantaneous amplitude. Furthermore, the inclusion of the additional two features, shown in (4) and (5), provide a more accurate statistical representation of the sEMG TFD [17] and improve the performance of the model.

System Based Modeling of Human NMS System

An ARMAX model [30] is used to map the sEMG features (i.e. inputs) to either the subject's grip force or length of fingertip travel (i.e. outputs). The equation for the system is

$$A(q)y(t) = B(q)u(t) + C(q)e(t) \tag{6}$$

where $y(t)$ is the output, $u(t)$ is the vector of inputs, and $e(t)$ is the model disturbance. The polynomials $A(q)$, $B(q)$, and $C(q)$ are given by

$$\begin{aligned} A(q) &= 1 + a_1 q^{-1} + ... + a_{n_a} q^{-n_a} \\ B(q) &= b_1 + b_2 q^{-1} + ... + b_{n_b} q^{-n_b+1} \\ C(q) &= 1 + c_1 q^{-1} + ... + c_{n_c} q^{-n_c} \end{aligned} \tag{7}$$

where n_a, n_b, and n_c are their orders. Each muscle was modeled as a second order process [31] such that the order of the polynomials were selected to be 14 for $A(q)$ and 13 for $B(q)$ and $C(q)$.

For the isometric grasping task, the first eight seconds of data, called the *fresh data set*, were used to train the reference model, called the *fresh model*, which captured the dynamics of the subject's least fatigued state. The remaining data was segmented into four second long windows with two seconds of overlap. The repetitive finger movement task utilized a twelve second long *fresh data set* for model estimation. The subsequent data was segmented into six second long windows with two seconds of overlap.

Monitoring of Performance Degradation

A distribution of one-step ahead prediction errors is generated by the *fresh data set* and *fresh model*. This *fresh error distribution*, p_1, is used as a reference to monitor the changes in system dynamics over time. As subsequent data is fed into the *fresh model*, *updated distributions*, p_2, of the latest one-step ahead prediction errors are computed. Under circumstances where the NMS system dynamics remain unaltered, p_1 and p_2 should be very similar. However, as the subject becomes tired, temporal changes in his system dynamics will manifest as deviations between the fresh and updated error distributions. This is because the fresh model will not adequately describe the subjects fatigued state. Thus, the difference between distributions p_1 and p_2 can be calculated using the Kullback-Leibler divergence given by

$$FSI = D_{KL}(p_1||p_2) = \sum_{i=1}^{N} ln(\frac{p_1}{p_2}) \tag{8}$$

and referred to as the freshness similarity index (FSI) [17]. The FSI metric, whose value varies between 0, complete similarity between the distributions, and 1, complete dissimilarity, can be used to track the departure from normal system behavior. In essence, the FSI quantifies the degradation of system dynamics over time making it aptly suited to monitor neuromuscular fatigue.

4. Results

Isometric Grasping Task

Model Outputs— Hand dynamometer force outputs during three of the six isometric grasping tasks are shown in Figure 3. The prescribed target forces for which the subject attempting to maintain were $17.3N$ for the 40% MVC test, $8.6N$ for the 20% MVC day 1 test, and $6.4N$ for the 20% MVC day 2 test. The differences in force outputs for the 20% MVC tests arise from separate MVC evaluations performed on days one and three of testing. Unique MVC's for each day of testing ensures the relative effort the subject is prescribed to exert is reflective of his physiological condition on the corresponding day.

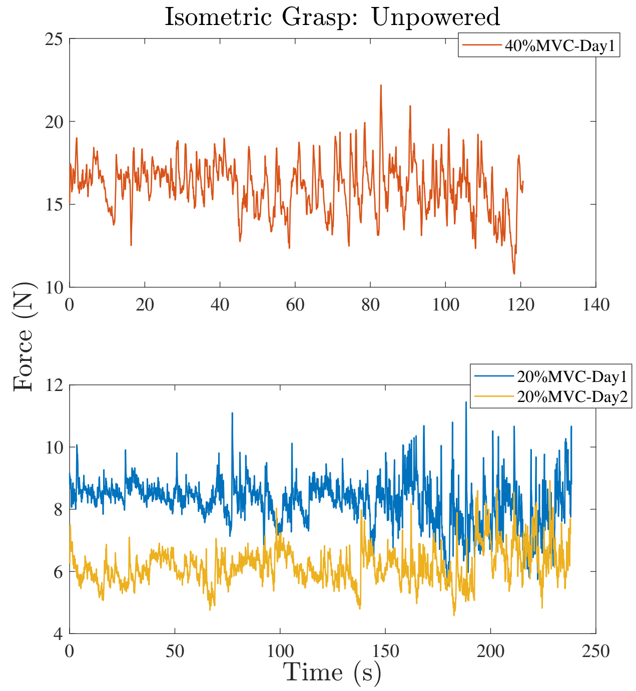

Figure 3. Subject's actual output grip forces from the hand dynamometer during three of the isometric grasping tests. All tests shown were performed when the SSRG was unpowered. From top to bottom the target forces the subject was prescribed to maintain were: $17.3N$**,** $8.6N$**, and** $6.4N$**.**

The 40% MVC test lasted for two minutes while the 20% MVC tests lasted for four minutes each. Although Figure 3 displays the true force values in Newtons, these values were normalized, from 0 to the maximum observed force within that test, before being used as outputs to the ARMAX model. Variation in the output force is seen to increase over time for all tests, providing evidence that the progression of fatigue made it difficult to maintain a constant grip force toward the end of the experiments. Cycles of the subject becoming tired and noticing his grip force dropping, squeezing the hand dynamometer harder to restore the force back to target level, then getting tired and allowing the force to drop again, are especially evident toward the end of the 40% MVC test.

Feature Extraction for Model Inputs— For all unpowered SSRG isometric grasp tests (i.e. 20% MVC day 1, 40% MVC day 1, and 20%MVC day 2), all six muscles showed statistically significant decreasing linear trends in the instantaneous frequency feature, $< f^1|t >$, ($p<0.001$). Furthermore, five out of six muscles showed significant increasing linear trends in instantaneous energy, $< f^0|t >$. For the 20% MVC day 1 powered SSRG isometric grasp test, three out of six of the muscles showed statistically significant increasing trends in instantaneous energy and four out of six showed statistically significant decreasing trends in instantaneous frequency ($p<0.001$). The 40% MVC powered SSRG isometric grasp test resulted in five of six muscles displaying statistically significant increasing trends in instantaneous energy and all six muscles revealing statistically significant decreasing trends in instantaneous frequency ($p<0.001$). Lastly, all six muscles showed statistically significant increasing linear trends in instantaneous energy and decreasing linear trends in the instantaneous frequency ($p<0.001$).

These observed trends in sEMG features during the isometric grasping tests are consistent with existing conventional methods of detecting fatigue at the muscular level. Since the majority, if not all, of the muscles revealed manifestations of fatigue, there is proof that the subject was tiring during all of the tasks. Thus, any evidence of fatigue given by the progression of changes in dynamic NMS system behavior using the presented system-based modeling technique, a process which not only evaluates the muscular inputs, but the relationship between these inputs and the biomechanical outputs, is well substantiated.

System Based Monitoring of Performance Degradation—The FSI for all six of the unpowered and powered isometric tests displayed statistically significant increasing slopes ($p<0.001$) (Table 1). Representative FSIs for the unpowered isometric grasping tests are shown in Figure 4. A significant increasing trend in FSI reflects increasing one-step ahead prediction error distributions between the subjects *fresh* state and his state at subsequent moments in time. The increasing slopes of the FSIs signify departures from normal NMS system behavior over the course of each task. Thus, the FSI is shown here to effectively monitor neuromuscular fatigue during an activity that requires an object to be held with a constant grasp force for an extended period of time.

The FSI metric exhibited consistency across multiple days of testing. The two days of unpowered 20% MVC testing consisted of grip force requirements that were very similar, only differing by about $2N$ (Figure 3). Analogously, the corresponding FSI slope values were comparable across these two tests. This can be seen by the lower confidence bound of 20% MVC day 1 test soverlapping slightly with the upper confidence bound of 20% MVC day 2 test (Figure 4).

Another characteristic displayed by the FSI metric was its resolving power to discern different rates of fatigue for varying magnitudes of grasping effort. For instance, the $2N$ difference in grip force values between the 20% MVC day 1 ($\sim 8.6N$) and 20% day 2 ($\sim 6.4N$) tests is mirrored in the distinguishable difference between the mean trends in their respective FSIs, with 20% day 1 showing a slightly greater slope than that of day 2. Furthermore, the 40% MVC FSI slope, corresponding to a grip force of $16N$, approximately double that of either 20% MVC day, showed a distinctly greater slope compared to the other two tests.

Furthermore, the FSI metric displayed the capability of distinguishing between different glove conditions at higher levels of effort. To preface the following results, a more exhaustive study with a greater number of participants and active SSRG FSR sensors is necessary before claims can be made about the efficacy of the SSRG in reducing performance degradation during an isometric grasping task. Rather, the intention of this work is to convey the capability of the FSI metric in identifying disparities between glove conditions that could have effected the subject's rate of fatigue. As such, the subject

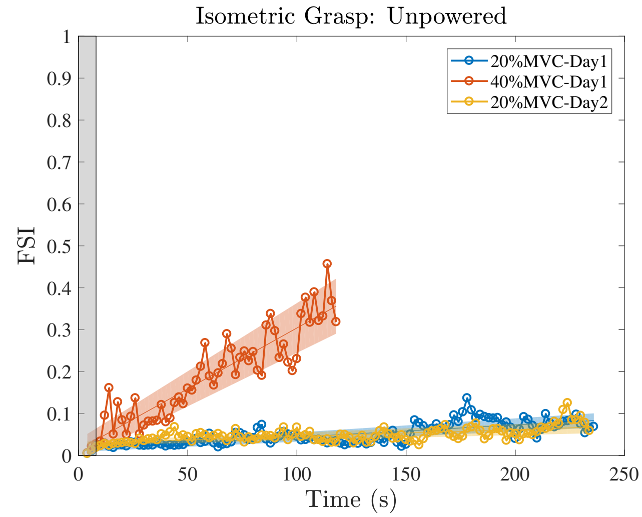

Figure 4. Calculated FSIs with trend lines and 95% confidence intervals during the unpowered SSRG isometric grasping task. The gray shaded region indicates the *fresh data* used to generate the reference model. Each task displayed a statistically significant increasing linear trend ($p<0.001$).

Table 1. FSI slopes over time during the isometric grasping task. "Unpow" signifies the tests performed while the SSRG was unpowered (i.e. not providing assistance), whereas "Pow" indicates the tests performed while the SSRG was powered (i.e. actively providing assistance). All slopes were statistically significant ($p<0.001$).

Test	Slope (Unpow)	Slope (Pow)
20% MVC day 1	$2.8909e10^{-4}$	$4.1357e10^{-4}$
40% MVC day 1	$2.9011e10^{-3}$	$1.0983e10^{-3}$
20% MVC day 2	$1.6482e10^{-4}$	$1.6925e10^{-4}$

showed a slower rate of performance degradation while the SSRG was powered compared to when it was unpowered for the 40% MVC day 2 test 1. The rate of fatigue for the 20% MVC day 2 test was approximately the same between the powered and unpowered SSRG conditions. As stated in the description of the pilot study, since the FSR sensors, which are best suited for the SSRG controller during isometric grasping tasks, were not active during these experiments, it is possible that the minimal assistance that the string-potentiometer-driven control mode provides during grasping tasks is more noticeable during a higher effort endeavors. The FSI slope value for the powered 20% MVC day 1 test is much higher than the unpowered test. This is most likely due to either the subject having inadequate time to rest between the end of the previous test (i.e. the 20% MVC powered SSRG trial) and the start of this test, or the window of fresh data used to build the model being too small and not fully capturing the subjects unfatigued dynamics.

Repetitive Movement Task

Model Outputs—The time series of fingertip travel, taken from the string potentiometer in the index finger of the SSRG, is displayed in Figure 5. This output data was normalized to reside between 0 and and maximum finger extension, then demeaned before being used in the ARMAX model. The

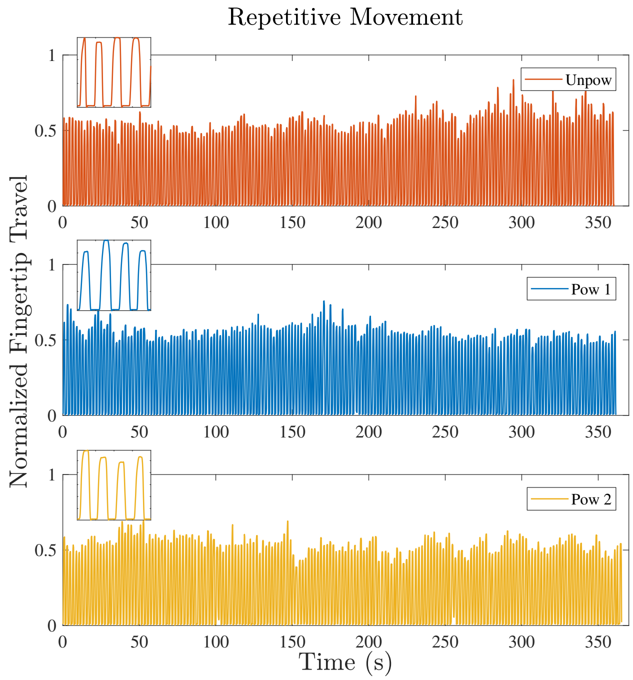

Figure 5. **Normalized fingertip travel from index finger of the SSRG during the repetitive movement task. From top to bottom the plots show the unpowered SSRG test, first powered SSRG test, and second powered SSRG test. Subplots in the upper left corners depict the first eight seconds of movement during each test and are included for a more detailed representation of finger position changes.**

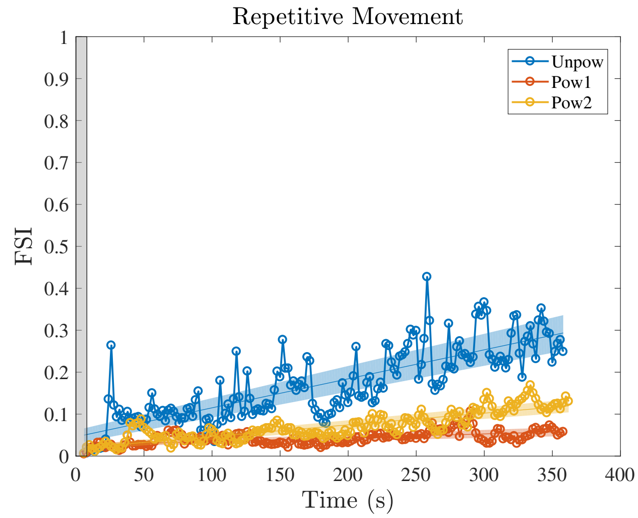

Figure 6. **Calculated FSIs with trend lines and 95% confidence intervals during the repetitive movement test. The gray shaded region indicates the *fresh data* used to generate the reference model. Each task displayed a statistically significant increasing linear trend (p<0.001).**

subject exhibited approximately the same amount of maximal fingertip travel for each of the repetitive motion tests.

Feature Extraction for Model Inputs— The first powered SSRG test, which was the first of three repetitive movement tests performed and will be referred to as "Pow 1", resulted in three of six muscles displaying statistically significant decreasing linear trends in instantaneous frequency and one muscle revealing statistically significant increasing linear trends in instantaneous energy ($p<0.001$). The next test, during which the subject used the SSRG while it was unpowered, showed four of six muscles exhibiting statistically significant decreasing linear trends in instantaneous frequency and two of six muscles displaying statistically significant increasing linear trends in instantaneous energy ($p<0.001$). For the second powered SSRG test, referred to as "Pow 1", four of six muscles exhibited statistically significant decreasing linear trends in instantaneous frequency, whereas all six muscles displayed statistically significant increasing linear trends in instantaneous energy ($p<0.001$).

Compared to the isometric grasping task, the repetitive movement task revealed fewer features with statistically significant trends in instantaneous frequency and instantaneous energy. It is possible that the subject did not experience a large resistive load opposing his hand movement. To perform the task the subject merely had to fight against the stiffness of the space suit glove in order to flex and extend his fingers. Although this resistance is by no means negligible, the subject confirmed that repetitively opening and closing his hand felt like it required less effort than maintaining a constant gripping force.

System Based Monitoring of Performance Degradation—As with the isometric grasping task, the FSI metric was successful in concisely tracking the temporal changes in subject dynamics during the repetitive movement task. FSIs for both the unpowered and powered SSRG tests demonstrated statistically significant increasing slopes ($p<0.001$) (Table 2) which can be seen in Figure 6. To reiterate, a significant increasing trend in FSI reflects departure from normal NMS system behavior over time, a phenomenon indicative of fatigue.

The order in which the repetitive movement tests were performed, as well as the amount of rest separating them, seemed to be reflected in the behavior of the FSI metric. The sequence of tests proceeded as follows: powered SSRG (Pow 1), unpowered (SSRG), and powered SSRG (Pow 2). The FSI slopes for the unpowered and second powered (Pow 2) tests are noticeably larger than the slope for the first unpowered condition (Pow 1). Although the subject rested for 10 to 15 minutes before proceeding to the next test, it may not have been enough time to minimize the effects of residual fatigue on subsequent tests. Thus, the accumulation of fatigue could have caused the subject to tire at an expedited rate during later experiments.

Furthermore, the FSI metric once again displayed the capability of distinguishing between different glove conditions. It seems that the subject's performance degraded quicker during the unpowered SSRG tests compared to the two powered SSRG tests. Although it is possible that the SSRG assistance during the second powered test, which was the last of the three tests to be performed, aided in reducing the amount of effort required top open and close the hand, a more exhaustive study with a greater number of participants is necessary before such claims can be made about the efficacy of the device. Nevertheless, these experiments revealed the promising capability of the FSI metric to consolidate and track the subject's state of fatigue during a series of tests requiring dynamic limb movement.

Table 2. FSI slopes over time during the repetitive movement task. "Unpow" signifies the condition in which the SSRG was unpowered (i.e. not providing assistance), whereas "Pow 1" and "Pow 2" represent the first and second conditions when the SSRG was powered (i.e. actively providing assistance) .All slopes were statistically significant (p<0.001).

Test	Slope
Unpow	$6.9179e10^{-4}$
Pow 1	$8.9651e10^{-5}$
Pow 2	$2.7911e10^{-4}$

5. Conclusions and Future Work

This paper presents the application of system-based monitoring for performance tracking of the human NMS system during space suit glove use. Time-frequency features from muscle sEMG signals and biomechanical measurements were used to build a model that characterized the system dynamics. A succinct representation of performance degradation, called the FSI, compared one-step ahead prediction errors of the model over time to quantify and track the divergence of current NMS system behavior to that of an unfatigued state. The efficacy of performance tracking during EVA style tasks were evaluated on pilot data collected from one subject across three days of testing. During isometric grasping and repetitive movement tasks, the subject displayed statistically significant increasing trends in the dissimilarity of the NMS models with respect to the least fatigued state, which implies that fatigue was developed over time. The trends exhibited during the isometric task revealed consistency across testing days and sensitivity in detecting differences in grip load requirements imposed upon the subject. Moreover, trends in the repetitive movement task proved effective in discriminating between different glove conditions, i.e. the presence and absence of robotic grip assistance. These system-based methods of fatigue monitoring were corroborated by conventional methods of quantifying muscle fatigue using sEMG spectral features.

The presented methodology for characterizing changes in the NMS system has the potential to monitor the physiological status of individuals during manned space exploration missions. This method can be implemented for assessing human health, recognizing the onset of abnormal performance, and evaluating fitness-for-duty, all of which are important for ensuring space mission safety and success.

Future avenues of research can provide enhancements to the current methodology and further substantiate the conclusions made in this paper. First, changes in the NMS system behavior can be characterized at the muscular level by recursively updating the parameters of the ARMAX model as new data is observed. Thus, the similarity between the updated models, which reflect the changes in underlying system dynamics over time, and the fresh model can be calculated using the frequency responses of their transfer functions. This information would be used to infer how the muscles involved in the movement influence the changes in dynamic system behavior over time [16], [17] and could be beneficial in diagnosing the root cause of fatigue. Second, the assumption of a linear relationship between NMS system inputs and outputs could be lifted. Although the method presented in this paper is analytically tractable, it is not fully appropriate for a complex physiological system. Nonlinear dynamic models could improve the estimation of the NMS system and provide more accurate performance tracking. Next, incorporating the synergistic activity of muscles into the system dynamics would aid the model's robustness to unexpected sEMG behavior. This is especially true for areas of the body containing muscles with redundant functionality, exemplified by the multi-layered forearm muscle complex which controls finger and wrist movement. Lastly, although the system-based modeling approach performed well during this less-than-optimal pilot study, expanding the scope of experimentation to a full human subject study is necessary to confidently draw conclusions about how individuals fatigue while wearing space suit gloves. A full study would require multiple subjects, a pressured glove box to more accurately assess the conditions experienced during EVA missions, and possibly active SSRG FSR sensors to enhance isometric grasping assistance if this glove were to be used for the study.

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