Assessment of Neuromuscular Fatigue from Muscle Synergies in Hand Poses ⋆

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Abstract: Surface electromyography (sEMG) is a common sensing modality for volitional control of robotic exoskeletons for the hand. However, neuromuscular fatigue can inhibit the reliability of sEMG-based control of robots, especially during prolonged use. Fatigue-awareness is needed for sEMG-based robotics to be viable for long-term motor augmentation, assistance, and rehabilitation. Prior works have explored time-frequency sEMG metrics indicative of fatigue, which are computationally expensive. Alternatively, sEMG analysis in the 'synergy'-domain can provide reliable, lower-dimensional metrics of neuromuscular fatigue from spatio-temporal patterns in muscle activation. Still, while much research effort has been expended towards synergy-domain sEMG analysis of lower limbs, work remains to establish the viability of synergy-domain sEMG analysis for fatigue-awareness during hand poses. In this manuscript, we present the assessment of neuromuscular fatigue via synergy-domain sEMG analysis in a pilot study with five healthy participants. We obtain time-frequency benchmarks and synergy-domain metrics of fatigue from sEMG data collected from the Flexor Digitorum Profundis, Flexor Pollicis Longus, and Extensor Digitorum Communis muscles during hand poses to illustrate that synergy-domain analysis is a reliable method to assess hand neuromuscular fatigue. We thereby show that synergy-domain sEMG analysis is viable for fatigue-aware hand exoskeleton control.

Keywords: Assistive and Rehabilitation Robotics; Human-Machine and Human-Robot Systems; Control Applications

1. INTRODUCTION

Robotic exoskeletons have been proposed to augment, assist, and restore hand function during prolonged exertion or after neuromuscular impairment. Force, torque, and position sensing have been explored for exoskeleton control, but one such modality, surface electromyography (sEMG), provides measurements of wearer neuromuscular activity ahead of movement (Singh et al. (2012)). In applications ranging from motor rehabilitation to astronaut EVA assistance, sEMG-based robotics can assist in preserving human health and safety (Rose et al. (2021)).

However, sEMG-based characterization accuracy is sensitive to neuromuscular fatigue as the central nervous system (CNS) alters motor control after prolonged exertion. Time-frequency metrics assessing fatigue have taxing computation, poor signal-to-noise ratio, and severe losses in reliability with neuromuscular fatigue (Madden et al. (2021); Ortega-Auriol et al. (2018); Singh et al. (2012); Lin et al. (2020); Zeng et al. (2021)).

Robust exoskeleton control in the presence of fatigue remains an open question, and without a solution, the risk of injury in prolonged human-robot interaction remains high (Madden and Deshpande (2017); Lin et al. (2020)).

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1.1 Background

Time-frequency analysis has been used to detect neuromuscular fatigue from sEMG data. Analysis in this domain provides metrics that are robust to statistically non-stationary 'dynamic' muscle contractions, revealing trends in spectral metrics including signal energy (Madden and Deshpande (2017)) that directly correlate to neuromuscular fatigue. However, this method requires time-consuming domain transforms and computation, requiring large memory storage capabilities which make it impractical in many human-robot interaction paradigms.

Neuroscience approaches have suggested 'synergy'-based analysis of muscle activity data to improve sEMG-based control during fatigue (Overduin et al. (2008)). In this domain, the CNS is thought to coordinate muscle activation by 'exciting' a small set of motor 'primitives' (Scano et al. (2018)) to excite groups of muscles that act synergistically to produce movement (Ortega-Auriol et al. (2018)). These primitives are developed by the CNS over time, organized and maintained subconsciously, such that they remain unaffected by transient influences like muscle fatigue.

Prior studies have shown that analysis of the structure and magnitude of these synergies in sEMG data (Liu and Wu (2010); Yağmur et al. (2017)), can enable low-dimensional analysis of muscle activity that remains robust to neuromuscular fatigue. Synergy-domain analysis and on-line classification of muscle signals thus provide promising avenues to robotic assistance over long durations.

1.2 Motivation

Synergy domain sEMG analysis of motor function has been well-explored for lower-limb muscle activity (Liu and Wu (2010); Yağmur et al. (2017)). Their utility in describing hand grasps has also been explored in other works (Alessandro et al. (2013); Overduin et al. (2008)).

However, there remains a significant gap in the characterization of muscle fatigue in functional hand grasps through synergy domain analysis. In this work we advance the state of the art by examining muscle fatigue during hand activity in the synergy domain, an understudied area of research that seeks to establish the practical utility of hand exoskeletons (Rose et al. (2021); Lin et al. (2020)) by reliably assessing muscle fatigue (Tresch et al. (2006)).

Through a pilot study (Section 2), we validate participants' muscle fatigue through force and time-frequency analysis. In Sections 3 and 4, we compare these results to analysis of lower-dimensional metrics in the synergy domain, demonstrating the separability of synergy domain effects associating increasing muscle fatigue and variation in hand pose. Concluding the analysis of this study, in Sections 4 and 5 we validate that synergy domain analysis of sEMG data enables reliable fatigue characterization and intent detection between hand poses. This is a first step towards a neuromuscular control and intent detection system for the hand that remains robust to fatigue (Fig. 1).

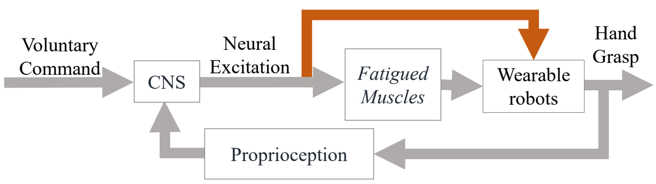

Fig. 1. Our goal is to assess sEMG data through synergy-domain analysis (red pathway), rather than time-frequency methods (pathway shown only in gray), which are obscured by muscle fatigue.

2. METHODS

The goal of this analysis was to validate the use of synergy domain analysis in identifying muscle fatigue in the power grasp, as well as to assess the separability of synergy domain features for four common hand grasps (Fig. 2). The experimental protocol employed in this study was approved by Auburn University's Institutional Review Board (22-080 EP). Per this protocol, five healthy males between 20 and 30 years of age with no known musculoskeletal or neuromuscular injuries participated in a voluntary study without compensation. The participants self selected their dominant hand for the study and provided written consent prior to the experiment.

2.1 Experiment Design

In this study, participants performed the Power Grasp (PG), Lateral Pinch (LP), Two Finger Pinch (TFP), and Three Finger Pinch (TFP) while holding a fluid-filled bulb dynamometer (Fig. 2). A pressure sensor connected to the dynamometer via a flexible tube was used to measure grasp pressure. As pressure-based hand dynamometry is a standard approach to measuring quasi-isometric grasp forces in rehabilitation medicine, the contractile dynamics of the dynamometer could be neglected (Maher et al. (2018)). To measure muscle activation signals, a portion of participants' forearm hair was removed using an electric razor, and single Delsys Trigno sEMG electrodes were applied to the participants Flexor Digitorum Profundis (FDP), Flexor Pollicis Longus (FPL), and Extensor Digitorum Communis (EDC) muscles.

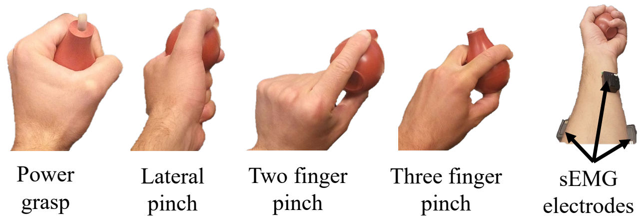

Fig. 2. Participants performed four hand poses, Power Grasp (PG), Lateral Pinch (LP), Two Finger Pinch (TFP), and Three Finger Pinch (TFP), while holding a pressure-sensing bulb dynamometer. Delsys Trigno sEMG Electrodes were placed at the FDP, FDL, and EDC muscles to measure muscle activation.

Two sets of trials were conducted, the first of which allowed for examination of the effects of fatigue during power grasp. Participants were instructed to squeeze the dynamometer as tightly as possible for three 60 second trials with 60 second rests in between each trial, to determine their maximum voluntary contraction (MVC) grasp pressure. Following a 60 second rest, participants were instructed to the hold the power grasp at a level of 70% of their MVC grasp pressure and were provided visual feedback via a live sliding plot window on a computer display. They were instructed to follow the visual feedback (a horizontal line denoting 70% MVC superimposed over a sliding window plot showing their grasp pressure) to maintain their exertion for three 60 second trials with 60 second rests between each trial. Immediately following each trial, participants were asked to provide a subjective estimate of their hand/forearm muscle fatigue as a score from one to ten with ten being extreme fatigue.

Subsequently, following 60 seconds of rest, after which participants recovered and reported no fatigue, the second set of trials were conducted to examine the separability of hand poses in the synergy-domain. Participants were asked to perform each of four hand poses (Fig. 2) for 30 seconds each, with 60 second rests in between each trial. Participants were asked to maintain grasp force and grasp timing to approximate activities of daily living (ie. holding a doorknob (power grasp), holding a door key (lateral pinch), picking up an object (two finger and three finger pinch). Visual feedback was provided as a live sliding plot window on a computer display and participants were asked to pace hand poses to one second intervals. Muscle activity in the fatigue trials and for the hand pose trials was recorded via Delsys data acquisition hardware at an average sampling rate of 1111 Hz.

2.2 Acquisition of sEMG Metrics

Three sets of metrics were obtained fromt the sEMG data and are presented in this study: 1. Time-frequency benchmarks of fatigue, 2. Synergy-domain metrics of fatigue, and 3. Synergy-domain metrics of pose separability.

Firstly, time-frequency metrics were acquired to establish the occurrence of fatigue. The Choi-Williams bilinear distribution, C, over time (t) and frequency (ω) was obtained (Eqn. 1) from the sEMG signal, x, using a signal-independent binomial kernel, $\Phi(\theta,\tau)$, for interference reduction (Eqn. 2). A well-established metric of fatigue, the instantaneous energy of the distribution, $a_i(t)$, was obtained through calculation the zero-order moment of C in 1 second epochs (Eqn. 3) (Overduin et al. (2008); Madden and Deshpande (2017)) and was smoothed with a first order sliding window Savitzky-Golay filter (Fig. 4).

$$C = \iiint_{-\infty}^{+\infty} x(u+\frac{\tau}{2})x^*(u-\frac{\tau}{2})\Phi e^{-j(\theta(t-u)+\tau\omega)}d\tau\, du\, d\theta \quad (1)$$

$$\Phi(\theta,\tau) = e^{-2pij\theta\tau} \quad (2)$$

$$|a_{\mathrm{i}}(t)| = \sqrt{\int (C(t,\omega))d\omega} \quad (3)$$

Second, synergy-domain metrics of fatigue and pose separability were obtained via bi-linear matrix decomposition. Non-negative matrix factorization (NMF) was selected for improved performance over principle components analysis, factor analysis, and independent component analysis across variance, occurrence of agreement, and dissimilarity for extracting synergies from isometric and dynamic muscle activity (Rabbi et al. (2020); Tresch et al. (2006)). NMF (Eqn. 4) and sEMG signals, V, were factored into W and H, where W contains activation coefficients of motor primitives, and H was found by error minimization (Eqn. 5). Rank three was selected for the NMF algorithm, signifying the selection of three muscle synergies, which described 85.51% of the Variance Accounted For (VAF) in the sEMG signals (Eqn. 6) (Tresch et al. (2006)).

$$V = W \cdot H \quad (4) \qquad ||V - W \cdot H|| = 0 \quad (5)$$

$$VAF = 1 - \frac{||(V - W * H)^2||}{||V||^2} \quad (6)$$

Finally, we demonstrate that synergy activation, W, lower in dimensionality than motor primitives, H, retains separable features that remain unaffected by neuromuscular fatigue (Fig. 6), becoming an interesting target for classification with minimal fatigue-related distortion even during intense muscle fatigue. Classification of synergy primitives during different phases of movement can also be carried out via machine-learning methods including Support Vector Machines (SVM), as well as neural networks, and is explored in other works (Zhao et al. (2021)).

3. RESULTS

Participant muscle fatigue was established with grasp pressure, measured throughout the three 70% MVC trials (assumed quasi-isometric so that muscle body dynamics are neglected (Madden et al. (2021))), and subjective ratings of fatigue (SRFs) in the hand and forearm from one to ten. Participant normalized grasp pressures (nGP) from each of the three fatigue trials were recorded as a percentage of 70% MVC grasp pressure threshold (Fig. 3). For one characteristic participant, nGP fell by approximately 10.7% from the first trial and third trial, and SRF for all participants increased by approximately 50% (Fig. 3).

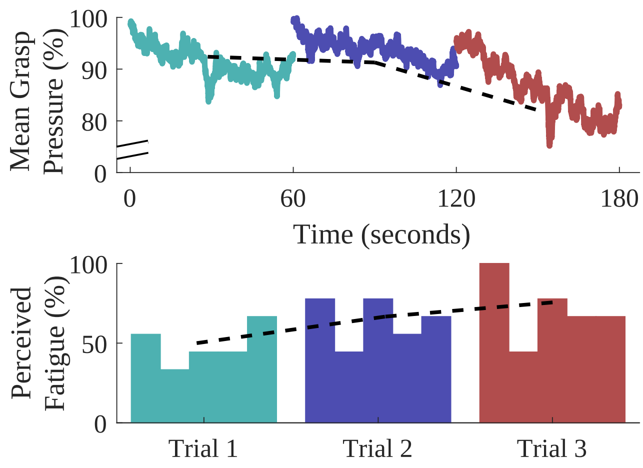

Fig. 3. The mean normalized grasp pressure for a characteristic participant (nGP, Top) decreased by approximately 11%, and the rated fatigue (SRF, bottom), increased by approximately 50% for all participants, indicating fatigue-related functional deficits.

Subsequently, instantaneous amplitude, $a_{\mathrm{i}}(t)$ of the time-frequency distribution of sEMG data was calculated in 10 ms epochs. This metric increased throughout each trial, with rates of increase also increasing between trials (Fig. 4)

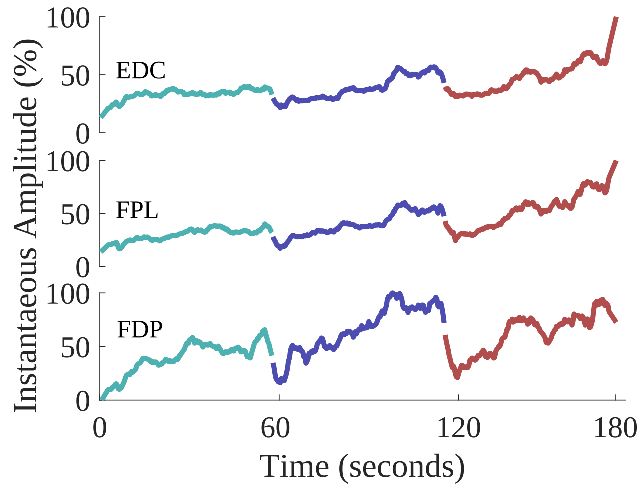

Fig. 4. Increasing instantaneous amplitude of the sEMG time-frequency distribution for EDC, FPL, and FDP muscles illustrate fatigue during the trials. Sixty second rests periods between trials are not shown.

Finally, synergy-domain metrics, including motor primitives for three muscle synergies and their corresponding activation coefficients, were collected for the fatigue trials and for the four hand poses in 10 ms epochs. From these metrics, the average activation coefficient for all participants at the start and end of each of the three trials were collected, and a decreasing trend in activation coefficients was observed (Fig. 5). Further, the structure of each of the three motor primitives for all participants were averaged for each trial, and it was found that the motor primitives did not vary significantly between trials (Fig. 5). A 3-dimensional space was constructed from the activation coefficients of each synergy for the for hand poses, allowing for graphical indication of the separability of four hand poses as a function of synergy (Fig. 6).

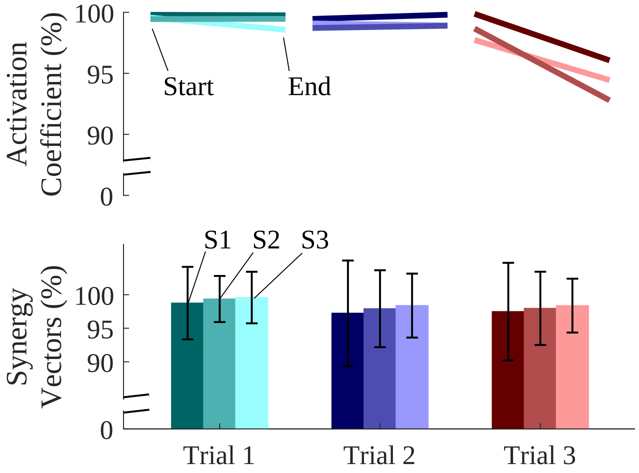

Fig. 5. Activation coefficients for each synergy (lines) generally decreased by 5-10% between the start and end of each trial, while the synergy structures (bars) did not vary significantly between trials.

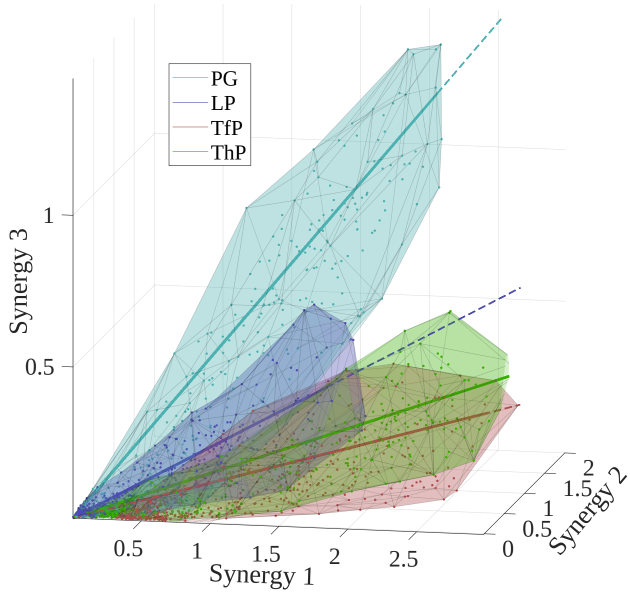

Fig. 6. 3D boundaries built using synergy activation coefficients from all participants for four poses is shown along with regression lines from singular value decomposition, illustrating synergy-domain separability.

The synergy compositions of each pose, illustrated graphically in Fig. 8, is clarified in Fig 7, indicating dimensions and sub-features that can be classified and analyzed for intent detection. Within this 3-dimensional synergy-space, it is also possible to quantify the changes in activation for the synergies composing the power grasp (PG) hand pose before and after fatigue trials (Fig. 8). Within this space, it was evident that significant reductions in synergy activation occur with fatigue, but that the synergy composition and structure did not significantly vary, supporting the results of the 2-dimensional analysis shown in Fig 5.

In summation, reductions in mean synergy activation were when fatigued and systematic variation in synergy activation between hand poses were observed in all participants.

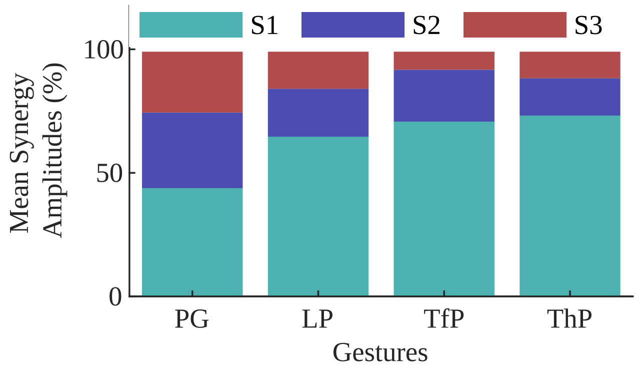

Fig. 7. The hand poses analyzed in this study were shown to occupy unique regions of a 3-dimensional synergy-space (Fig. 6), implying that the hand poses were 'composed' of varying combinations of the three synergies. In the above figure, this is further clarified by showing the average proportions of each synergy that composed poses. This result further illustrates the separability of hand poses in the synergy-domain.

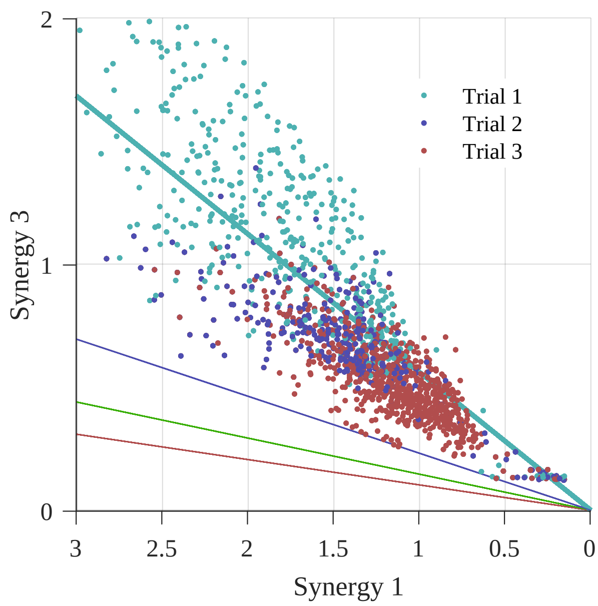

Fig. 8. Systematic reduction in synergy activation between fatigue trials one and three is clearly evident in 3D space of synergies. Above, the view of the 3D plot is limited to two axes to illustrate this trend.

4. DISCUSSION

In this study, the presence of neuromuscular fatigue was investigated in the time-frequency- and synergy-domain for five subjects performing a power grasp hand pose three times in 60 second intervals. Further, the synergy-domain separability of four common hand poses repeated over 30 second trials was studied. The results of this study indicated that while layers of analysis including data segmentation, network- or learning-based classification, and spectral analysis are required to provide time-frequency sEMG metrics robust to fatigue (Britt et al. (2021); Madden et al. (2021)), low-dimensional synergy-domain metrics remain robust to fatigue (Figs. 5,6).

4.1 Outcomes of this study

In analyzing muscle fatigue, time-frequency analysis indicated that signal energy, a marker of fatigue, increased from the first to the third trial for all muscles assessed (Fig 4). Less change was observed for the EDC muscle, as expected for the flexion-based hand poses examined. The observed increase indicated occurrence of fatigue (Madden and Deshpande (2017)), however without force and kinematic sensing, it can't be differentiated from changes in pose, or other neuromuscular impairment (Torres-Oviedo and Ting (2010)).

By contrast, analysis in the synergy-domain described systematic neuromuscular adaptations taken by the motor cortex in response to fatigue. In this domain, 3x600 sEMG vectors produced 3x3 synergy excitation vectors representing excitation of three synergies and 3x60 excitation primitive vectors representing the three synergy primitives, where three synergies accounted for an average of 85.51% of signal variance (VAF) with maximum mean squared approximation error of less than 1% (Santello et al. (1998); Mason et al. (2001); Jarque-Bou et al. (2019); Zhao et al. (2021)). Synergy excitation to the muscles decreased for every participant from trial one to trial three (Fig 5), indicating an automatic response to fatigue between the first, second, and third trials. This was consistent with the time-frequency and self-reported metrics.

In analyzing gestures, synergy activation coefficients were mapped in a 3-dimensional space, where trends in activation were clearly discernable. As summarized graphically (Fig. 6), the space of synergies illustrated well-separable features that retained their integrity in the presence of muscle fatigue (Fig. 8). These results indicate that hand pose variations are achieved through trackable changes in synergy excitation, a coherent motor control strategy that is consistent and distinguishable.

The structure of the synergy primitives were very similar between participants and did not vary significantly between fatigue trials (Fig. 5,7). This indicates that the response of the central nervous system to fatigue did not include re-organization of underlying motor primitives, but rather that adaptation to neuromuscular fatigue was limited to the amplitude of the excitation delivered to these primitives. This result is consistent with the literature (Ortega-Auriol et al. (2018)), and suggests the repeatability of synergy domain analysis for fatigue estimation (Zhao et al. (2021); Torres-Oviedo and Ting (2010)).

4.2 Exoskeleton Control Implications

To maximize desirable human-only dynamics, thermal and electrical efficiency, and robot functional lifespan, sEMG-based control may be structured in minimally-assist, assist-as-needed, shared-autonomy, and other optimal-control paradigms. Such control schemes are especially relevant in remote environments, such as in astronaut EVAs (Gernhardt et al. (2008); Madden and Deshpande (2017)), and rehabilitation applications (Boyasab and Guévela (2011)). Neuromuscular fatigue can reduce sEMG classification accuracy in such control architectures (Lin et al. (2020); Zeng et al. (2021); Madden et al. (2021)).

In this work, we have demonstrated the utility of synergy-domain metrics including activation coefficients of individual muscle synergies in characterizing fatigue and movement intent. We thereby suggest that synergy activation coefficients can be used as control inputs for fatigue and intent assessment and classification. This approach could establish exoskeleton control that is robust to fatigue.

4.3 Limitations

In this study, redundancy in data analysis through kinematic, psychophysical, time-frequency, and finally synergy-domain analysis provides confidence in our claims. However, this pilot study has limitations which may impact the clarity of the results presented. Firstly, we used the commonly sourced bulb dynamometer which had minimal deformation during hand poses. However, as it is compliant, some non-uniform grasp dynamics may be present between participants. This could be addressed through repetition of the trials with purely rigid instrumentation. Further, we did not assess fatigue across multiple poses, but only power grasp.

4.4 Future Work

To build upon the results presented in this manuscript, future work should include exploring the conclusions reported above, as well as toward implementing these results in hand exoskeleton control. These steps include evaluation of the conclusions in truly isometric conditions with specialized force-sensitive rigid instruments and through repetition of this study across multiple hand grasps, and across a wider demographic range. Concurrently, we are working to implement online sEMG-based control using synergy-domain metrics in fatigue contexts and in activities of daily living.

5. CONCLUSION

In this work, we show that the reduction in the excitation of three dominant muscle synergies provides a reliable way to quantify hand muscle fatigue, as well as movement intent, and that these trends trends remain observable and retain their integrity in the presence of hand neuromuscular fatigue. By comparing these results across trials and across participants (Fig. 5), we show that this phenomenon represents a systematic neuromuscular control strategy to account for fatigue, which can be tracked, quantified, and utilized for exoskeleton control.

We illustrate these metrics (Fig. 6, 7, 8) to provide context regarding their separability in an experimental trial. Through this analysis, we show that synergy domain characterization of muscle activity is suitable for controlling fatigue-aware robotic exoskeletons, representing a step towards establishing reliable exoskeleton control for human hand augmentation and assistance.

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