

**MUSCLE SYNERGY-BASED FUNCTIONAL
ELECTRICAL STIMULATION AND PREDICTIVE
MODELLING IN POST-STROKE MUSCLE FATIGUE
MANAGEMENT**

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INDIAN INSTITUTE OF TECHNOLOGY DELHI**

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by

SMRITI BALA

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Submitted

**in fulfillment of the requirements of the degree of
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CERTIFICATE

This is to certify that the thesis titled “**MUSCLE SYNERGY-BASED FUNCTIONAL ELECTRICAL STIMULATION AND PREDICTIVE MODELLING IN POST-STROKE MUSCLE FATIGUE MANAGEMENT**” submitted by **Ms. Smriti Bala**, to the Indian Institute of Technology, Delhi, for the award of the degree of **Doctor of Philosophy in Biomedical Engineering**, is a bonafide record of the research work done by her under my supervision and guidance. The thesis work, in my opinion, has reached the requisite standard. The contents of this thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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DECLARATION OF PUBLISHED CHAPTERS

I, Smriti Bala, hereby declare that the contents of the following chapters in this thesis have been published in the following respective journals. The published content has been included in the thesis according to the chronology given below.

Published Chapters

1. Chapter 2: Instrumentation and Development of Muscle Synergy-based FES

- **Published as:** S. Bala, V. Y. Vishnu, and D. Joshi, “Muscle Synergy-based Functional Electrical Stimulation Reduces Muscular Fatigue in Post-stroke Patients: A Systematic Comparison,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, pp. 1–1, Jun. 2023, doi:10.1109/tnsre.2023.3290293.

2. Chapter 3: Fatigue Assessment with Muscle Synergy-based FES in Post-stroke Patients: Implementation and Comparison with Conventional Methods

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3. Chapter 4: MEFFNet: Forecasting Myoelectric Indices of Muscle Fatigue in FES Induced Dynamic Contractions

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4. Chapter 5: Summary, Limitations, and Future Scope

- Contains information derived in parts from the published works referenced in Chapters 2, 3, and 4.

I certify that the above declaration is accurate and that I have adhered to applicable institutional and copyright policies in the preparation of this thesis.

Date:

Smriti Bala

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Smriti Bala

ABSTRACT

Stroke, a cerebrovascular event associated with the disruption of blood supply to the brain which aggravates neurological abnormalities, is the leading cause of death and major contributor to disability worldwide. A source of significant economic burdens, it can also lead to a range of post-stroke complications and consequences of which physical impairments such as hemiparesis has debilitating effects on the survivor's body. It affects the coordination and balance of the patients, hindering mobility and disrupting the ease of doing activities of daily living. To revert the state of paresis, immediate rehabilitation is an indubitable necessity. With this regard it has been unanimous that the maximum benefits of rehabilitation in restoring paralyzed limb can be reaped in the first six months post occurrence of stroke. In this regard, stimulation-based rehabilitation which induces functional movements, also termed as functional electrical stimulation (FES), has seen considerable success. The benefits of using FES include positive responses at cellular level, improved blood circulation, overall biomechanical enhancement, tissue regeneration, reversing long-term denervation muscle atrophy and dystrophy, increasing myofiber diameter size by more than ~50% and regenerating new myofibers.

However, with the above said advantages, FES comes with the challenge of rapid muscle fatigue on application. This stimulation induced muscle fatigue is believed to originate from reverse order of muscle fiber recruitment which occurs during stimulation unlike voluntary activation. The reverse recruitment order leads to faster fatigue development as more type II fibers are utilized earlier than with volitional control. Unmonitored stimulation-induced fatigue leads to excessive buildup of by-products of muscle contractions, excessive heat, tissue damage, fibers injury, electroporation etc. Although stimulation-induced fatigue is an inevitable process which cannot be stopped, precautionary measures can be taken to save the muscles from damage. The stimulation induced muscle fatigue depends upon the applied stimulation parameters (amplitude, pulse width, and frequency) which lacks consensus. Additionally, muscle fatigue is a gradual phenomenon; therefore, continuous monitoring is required during FES sessions to tailor or modify the stimulation parameters and ensure their optimization. Thus, the ill-effects of FES inducing muscle fatigue primarily revolve around lack of optimum stimulation patterns since the beginning of pulse application and lack of muscle fatigue predicting strategies which can help foresee its development. To address these important gaps, this thesis aims to investigate:

- The therapeutic benefits of a biomimetic/guided stimulation pattern designed to

mimic the physiological stimulation approach adopted by the central nervous system, with the hypothesis that such a stimulation template could induce less muscle fatigue and enhance functional outcomes, and

- A forecasting framework using a deep learning model to foresee the myoelectric indicators of muscle fatigue using stimulation evoked electromyography.

In this thesis experiments have been performed for single joint elbow flexion activity which is one of the crucial single joint activities of upper limb that helps in achieving or fulfilling activities of daily living such as eating, drinking, picking up objects, and many more. Previous research suggests the use of biomimetic ways of stimulation to address the issue of lack of standard stimulation patterns or templates. Such methods which mimic the natural ways of stimulation are considered guided stimulation patterns. Works done in the recent past found that guided stimulation patterns such as muscle synergy-based FES improved movement kinematics instantly and in long-term use in post-stroke patients. However, the therapeutic benefits and efficacy of muscle synergy-based FES patterns over traditional stimulation patterns needed exploration. Additionally, its role in muscle fatigue development compared to conventional patterns also needs investigation.

Therefore, in this thesis, a guided stimulation pattern based on muscle synergies was designed and developed to facilitate elbow flexion in sub-acute post-stroke patients. The study introduces an improved method for selecting a muscle synergy template to generate the FES waveform for elbow flexion. This method involves an objective assessment of intra-subject and inter-subject similarities in muscle synergies during elbow flexion across seven participants. By comparing these task-specific synergies and effective filtration of evoked surface electromyography (sEMG), the desired, biomimetic, synergy-based FES template was facilitated. This template was developed on calibration-based mapping of evoked EMG envelopes to FES parameters. This approach helped in the identification of FES parameters corresponding to muscle synergy-based reconstructed sEMG envelopes, representing a novel and previously unexplored method.

In subsequent study, the therapeutic benefits of muscle synergy-based FES were compared to traditional stimulation patterns from the perspective of muscular fatigue and kinematic performance produced. Three stimulation waveforms/envelopes: customized rectangular, trapezoidal, and muscle synergy-based FES patterns were administered on six post-stroke patients and six healthy individuals to achieve full elbow flexion. The muscular fatigue was measured through features of evoked sEMG, and the kinematic outcome was measured through angular displacement during elbow flexion. The time domain (peak-to-

peak amplitude, mean absolute value, root-mean-square) and frequency domain (mean frequency, median frequency) features also termed as myoelectric indices of fatigue were calculated from evoked-electromyography. Myoelectric indices of fatigue and peak angular displacements of elbow joint were compared across waveforms.

It was found that the muscle synergy-based stimulation pattern sustained the kinematic output for longer durations and induced less muscular fatigue followed by trapezoidal and customized rectangular patterns in healthy and post-stroke participants. These findings imply that the therapeutic effect of muscle synergy-based functional electrical stimulation stems from not only being biomimetic but also due to it being efficient in inducing less fatigue.

Further, a deep learning framework was developed to foresee indicators of muscle fatigue from evoked sEMG, i.e. forecasting of the myoelectric indices of muscle fatigue. The instant estimation of muscle fatigue using sEMG becomes challenging due to the progressive rather than instantaneous nature of fatigue development. Myoelectric indices forecasting has emerged as an important tool for muscle fatigue monitoring in wearable technologies, adaptive control of assistive devices like exoskeletons and prostheses, FES-based Neuroprostheses, and more. However, non-stationary temporal development of these indices in dynamic contractions makes forecasting difficult. Hence, incorporating transfer learning into a deep learning forecasting model could improve the prediction results.

Therefore, Myoelectric Fatigue Forecasting Network (MEFFNet), was designed to forecast these indices (both time and frequency domain) for voluntary and FES induced dynamic contractions in healthy and post-stroke subjects respectively. Different state-of-the-art deep learning models along with the novel MEFFNet architecture were tested on these indices obtained during - a) voluntary elbow flexion and extension with four different weights (1 kg, 2 kg, 3 kg, and 4 kg) in sixteen healthy subjects, and b) FES induced elbow flexion in sixteen healthy and seventeen post-stroke subjects under three different stimulation patterns (customized rectangular, trapezoidal, and muscle synergy-based).

A version of MEFFNet, named as pretrained MEFFNet, was trained on a dataset of sixty thousand synthetic time series to transfer its learning on real time series of myoelectric indices of fatigue. The pretrained MEFFNet could forecast up to 22.62 seconds (60 timesteps) into the future with a mean absolute percentage error of $15.99 \pm 6.48\%$ in voluntary contractions and $11.93 \pm 4.77\%$ in FES-induced contractions, significantly outperforming the MEFFNet and other models under consideration ($p < 0.05$, one-way repeated measures ANOVA). The results suggest combining the proposed model with wearable technology, prosthetics, robotics, and stimulation devices to enhance predictive

strategies and system responsiveness. The above work showed that transfer learning in time series forecasting has potential to improve wearable sensor predictions.

This thesis explores the development of a muscle synergy-based FES system, hypothesized to reduce stimulation-induced fatigue by leveraging the natural mechanisms involved in performing motor tasks. Building on this knowledge of selecting a biomimetic stimulation template for muscle fatigue reduction, a deep learning framework was introduced to predict myoelectric indices of muscle fatigue using sEMG signals which could be used to facilitate real-time monitoring and adaptive control, thereby advancing the strategies to mitigate stimulation induced muscle fatigue. The research methods and outcomes presented in this thesis provide valuable tools for researchers and physiotherapists to select effective stimulation patterns, thereby maximizing post-stroke rehabilitation benefits. Additionally, the ability to forecast fatigue indicators can inform real-time modifications of stimulation parameters. These advancements not only enhance the effectiveness of FES but also lay the groundwork for future real-time fatigue management, allowing for dynamic adjustments to ongoing FES sessions to optimize patient outcomes. The findings could improve FES therapy for post-stroke patients, promoting faster recovery and greater independence.

सार

स्ट्रोक (Stroke), मस्तिष्क में रक्त की आपूर्ति में व्यवधान से जुड़ी एक मस्तिष्कवाहिकीय घटना है जो तंत्रिका संबंधी असामान्यताओं को बढ़ाती है। स्ट्रोक दुनिया भर में मृत्यु और विकलांगता के प्रमुख कारणों में से एक है। यह आर्थिक बोझ का एक महत्वपूर्ण स्रोत है। यह मस्तिष्काघात के बाद कई जटिलताओं और परिणामों को भी जन्म दे सकता है, जिसके परिणामस्वरूप हेमिपेरेसिस जैसी शारीरिक क्षति जीवित बचे व्यक्ति के शरीर पर दुर्बल करने जैसे नकारात्मक प्रभाव डालती है। यह रोगियों के समन्वय और संतुलन को प्रभावित करता है, गतिशीलता में बाधा डालता है और दैनिक जीवन की गतिविधियों को करने में आसानी को बाधित करता है। पक्षाघात की स्थिति को पूर्व स्थिति में वापस लाने के लिए, तत्काल पुनर्वास एक अपरिहार्य आवश्यकता है। इस संबंध में यह सर्वसम्मत से माना गया है कि स्ट्रोक की घटना के बाद पहले छह महीनों में लकवाग्रस्त अंग को बहाल करने में पुनर्वास के अधिकतम लाभ प्राप्त किए जा सकते हैं। इस संबंध में, विद्युत उत्तेजना-आधारित पुनर्वास, जो कार्यात्मक संचलनों को प्रेरित करता है, तथा जिसे कार्यात्मक विद्युत उत्तेजना (एफईएस/FES) भी कहा जाता है, ने काफी सफलता देखी है। FES के उपयोग के लाभों में कोशिकीय (सेलुलर) स्तर पर सकारात्मक प्रतिक्रियाएँ, रक्त परिसंचरण में सुधार, समग्र बायोमैकेनिकल वृद्धि (जीव-यांत्रिकी में सुधार), ऊतक पुनर्जनन, दीर्घकालिक वितंत्रिकायन मांसपेशी शोष और डिस्ट्रोफी को उलटना, मायोफाइबर व्यास के आकार को ~50% से अधिक बढ़ाना और नए मायोफाइबर को पुनर्जीवित करना शामिल है।

हालाँकि, उपरोक्त लाभों के साथ, FES के अनुप्रयोग पर तेजी से मांसपेशियों में थकान की चुनौती भी आती है। माना जाता है कि विद्युत उत्तेजना से प्रेरित यह मांसपेशी थकान, मांसपेशी फाइबर रिक्रूटमेंट के रिवर्स ऑर्डर से उत्पन्न होती है, जो स्वैच्छिक सक्रियण के विपरीत विद्युत उत्तेजना के दौरान होती है। रिवर्स रिक्रूटमेंट ऑर्डर से तेजी से थकान का विकास होता है क्योंकि अत्यधिक टाइप II मांसपेशी फाइबर का उपयोग स्वैच्छिक सक्रियता की तुलना में पहले हो जाता है। अनियंत्रित विद्युत उत्तेजना की थकान से मांसपेशियों के संकुचन के उप-उत्पादों, अत्यधिक गर्मी, ऊतक क्षति, तंतुओं की चोट, इलेक्ट्रोपोरेशन आदि का अत्यधिक निर्माण होता है। हालाँकि विद्युत उत्तेजना की थकान एक अपरिहार्य प्रक्रिया है जिसे रोका नहीं जा सकता है, मांसपेशियों को नुकसान से बचाने के लिए एहतियाती उपाय किए जा सकते हैं। विद्युत उत्तेजना-जनित मांसपेशी की थकान लागू विद्युत उत्तेजना मापदंडों (आयाम, पल्स चौड़ाई और आवृत्ति) पर निर्भर करती है, जिसमें आम सहमति का अभाव है। इसके अतिरिक्त, मांसपेशियों की थकान एक क्रमिक घटना है; इसलिए, विद्युत उत्तेजना मापदंडों को अनुकूलित या संशोधित करने और उनके अनुकूलन को सुनिश्चित करने के लिए FES सत्रों के दौरान निरंतर निगरानी की आवश्यकता होती है। इस प्रकार, मांसपेशियों की थकान को उत्पन्न करने वाले FES के दुष्प्रभाव मुख्य रूप से पल्स एप्लिकेशन की शुरुआत से इष्टतम विद्युत उत्तेजना पैटर्न की कमी और मांसपेशियों की थकान की भविष्यवाणी करने वाली रणनीतियों की कमी के इर्द-गिर्द घूमते हैं जो इसके विकास की भविष्यवाणी करने में मदद कर सकते हैं। इन महत्वपूर्ण कमियों को दूर करने के लिए, इस थीसिस का उद्देश्य निम्नलिखित की जांच करना है:

- केंद्रीय तंत्रिका तंत्र द्वारा अपनाए गए शारीरिक उत्तेजना दृष्टिकोण की नकल करने के लिए डिज़ाइन किए गए बायोमिमेटिक/निर्देशित विद्युत उत्तेजना पैटर्न के चिकित्सीय लाभ, इस परिकल्पना के साथ कि इस तरह के विद्युत उत्तेजना टेम्पलेट

से मांसपेशियों की थकान कम हो सकती है और कार्यात्मक परिणाम बढ़ सकते हैं, और

- विद्युत उत्तेजना द्वारा जनित इलेक्ट्रोमायोग्राफी का उपयोग करके मांसपेशियों की थकान के मायोइलेक्ट्रिक संकेतकों का पूर्वानुमान लगाने के लिए एक गहन शिक्षण मॉडल का उपयोग करके एक पूर्वानुमान ढांचा तैयार करना।

इस थीसिस में सिंगल जॉइंट कोहनी फ्लेक्सन गतिविधि का प्रयोग किया गया है जो ऊपरी अंग की महत्वपूर्ण सिंगल जॉइंट या एकल संयुक्त गतिविधियों में से एक है तथा दैनिक जीवन की गतिविधियों जैसे कि खाना, पीना, वस्तुओं को उठाना और कई अन्य को प्राप्त करने या पूरा करने में मदद करती है। पूर्व अनुसंधानों में मानक विद्युत उत्तेजना पैटर्न या टेम्पलेट्स की कमी के मुद्दे को संबोधित करने के लिए विद्युत उत्तेजना के बायोमिमेटिक तरीकों के उपयोग का सुझाव दिया गया है। ऐसी विधियाँ जो विद्युत उत्तेजना के प्राकृतिक तरीकों की नकल करती हैं, उन्हें निर्देशित विद्युत उत्तेजना पैटर्न माना जाता है। हाल ही में किए गए कार्यों में पाया गया है कि मांसपेशी तालमेल-आधारित FES जैसे निर्देशित विद्युत उत्तेजना पैटर्न ने स्ट्रोक के बाद के रोगियों में तुरंत और दीर्घकालिक उपयोग में गति कीनेमेटिक्स में सुधार किया। हालांकि, पारंपरिक विद्युत उत्तेजना पैटर्न की तुलना में मांसपेशी तालमेल-आधारित FES पैटर्न के चिकित्सीय लाभ और प्रभावकारिता की खोज की आवश्यकता है। इसके अतिरिक्त, मांसपेशी थकान विकास में इसकी भूमिका की पारंपरिक पैटर्न की तुलना में भी जांच की आवश्यकता है।

इसलिए, इस थीसिस में, अनुत्तीव्र स्ट्रोक के बाद के रोगियों में कोहनी फ्लेक्सन को सुविधाजनक बनाने के लिए मांसपेशी तालमेल पर आधारित एक निर्देशित विद्युत उत्तेजना पैटर्न को बनाया और विकसित किया गया है। यह अध्ययन कोहनी फ्लेक्सन के लिए FES टेम्पलेट उत्पन्न करने हेतु मांसपेशी तालमेल का चयन करने के लिए एक बेहतर विधि प्रस्तुत करता है। इस विधि में सात प्रतिभागियों में कोहनी फ्लेक्सन के दौरान मांसपेशियों की तालमेल में “अंतर्व्यक्तिगत” या “विषय के भीतर” और “अंतर-विषय” या “विषयों के बीच” समानताओं का एक वस्तुपरक मूल्यांकन शामिल है। इन कार्य-विशिष्ट तालमेल और उत्पन्न सतह इलेक्ट्रोमायोग्राफी (एसईएमजी/sEMG) के प्रभावी निस्पंदन की तुलना करके, वांछित, बायोमिमेटिक, तालमेल-आधारित एफईएस टेम्पलेट को सुगम बनाया गया है। यह टेम्पलेट उत्पन्न ईएमजी आवरण के एफईएस मापदंडों के अंशांकन-आधारित मानचित्रण पर विकसित किया गया है। इस दृष्टिकोण ने मांसपेशी तालमेल-आधारित पुनर्निर्मित एसईएमजी आवरणों के अनुरूप एफईएस मापदंडों की पहचान करने में मदद की, जो एक नई और पहले से ना जाँची गयी विधि है।

बाद के अध्ययन में, मांसपेशियों की थकान और उत्पादित गतिज प्रदर्शन के परिप्रेक्ष्य से मांसपेशियों के तालमेल-आधारित FES के चिकित्सीय लाभों की तुलना पारंपरिक विद्युत उत्तेजना पैटर्न से की गई है। तीन विद्युत उत्तेजना आवरण: अनुकूलित आयताकार, समलम्बाकार, और मांसपेशियों के तालमेल-आधारित FES पैटर्न छह पोस्ट-स्ट्रोक रोगियों और छह स्वस्थ व्यक्तियों पर पूर्ण कोहनी फ्लेक्सन प्राप्त करने के लिए प्रशासित किए गए थे। मांसपेशियों की थकान को उत्पन्न sEMG की विशेषताओं के माध्यम से मापा गया है, और गतिज परिणाम को कोहनी फ्लेक्सन के दौरान कोणीय विस्थापन के माध्यम से मापा गया है। समय डोमेन (पीक-टू-पीक आयाम, औसत निरपेक्ष मूल्य, मूल-माध्य-वर्ग) और आवृत्ति डोमेन (माध्य आवृत्ति, औसत आवृत्ति) विशेषताओं को थकान के मायोइलेक्ट्रिक सूचकांक भी कहा जाता है, जिन्हें उत्पन्न-इलेक्ट्रोमायोग्राफी से गणना की गई है। थकान के मायोइलेक्ट्रिक

सूचकांक और कोहनी के जोड़ के शिखर कोणीय विस्थापन की तुलना आवरणों में की गई है।

यह पाया गया कि मांसपेशी तालमेल-आधारित विद्युत उत्तेजना पैटर्न ने लंबे समय तक गतिज परिणाम को बनाए रखा और स्वस्थ और स्ट्रोक के बाद के प्रतिभागियों में कम मांसपेशी थकान उत्पन्न की, जिसके बाद समलम्बाकार और अनुकूलित आयताकार पैटर्न ने नियत क्रम के अनुसार परिणाम को बनाए रखा। इन निष्कर्षों का तात्पर्य है कि मांसपेशी तालमेल-आधारित कार्यात्मक विद्युत विद्युत उत्तेजना का उपचारात्मक प्रभाव न केवल बायोमिमेटिक होने से है बल्कि कम थकान उत्पन्न करने में कुशल होने के कारण भी है।

इसके अलावा, उत्पन्न sEMG से मांसपेशी थकान के संकेतकों की भविष्यवाणी अर्थात् मायोइलेक्ट्रिक सूचकांकों का पूर्वानुमान करने के लिए एक डीप लर्निंग (डीएल) फ्रेमवर्क विकसित किया गया है। थकान के विकास की तात्कालिक प्रकृति के बजाय प्रगतिशील प्रकृति के कारण sEMG का उपयोग करके मांसपेशी थकान का तत्काल अनुमान लगाना चुनौतीपूर्ण हो जाता है। मायोइलेक्ट्रिक सूचकांक पूर्वानुमान, पहनने योग्य प्रौद्योगिकियों में मांसपेशियों की थकान की निगरानी, एक्सोस्केलेटन और कृत्रिम अंगों जैसे सहायक उपकरणों के अनुकूली नियंत्रण, एफईएस-आधारित न्यूरोप्रोस्थेसिस और बहुत कुछ के लिए एक महत्वपूर्ण उपकरण के रूप में उभरा है। हालांकि, गतिशील संकुचन में इन सूचकांकों का गैर-स्थिर समय-श्रृंखला-व्यवहार विकास पूर्वानुमान को कठिन बनाता है। इसलिए, डीप लर्निंग पूर्वानुमान मॉडल में ट्रांसफर लर्निंग को शामिल करने से पूर्वानुमान के परिणामों में सुधार हो सकता है।

इसलिए, मायोइलेक्ट्रिक थकान पूर्वानुमान नेटवर्क (मेफ़नेट/MEFFNet) को स्वस्थ और स्ट्रोक के बाद के विषयों में क्रमशः स्वैच्छिक और FES प्रेरित गतिशील संकुचन के लिए इन सूचकांकों (समय और आवृत्ति डोमेन दोनों) का पूर्वानुमान लगाने के लिए डिज़ाइन किया गया है। इन सूचकांकों पर विभिन्न अत्याधुनिक डीप लर्निंग मॉडल के साथ-साथ नए MEFFNet आर्किटेक्चर का परीक्षण - a) सोलह स्वस्थ विषयों में चार अलग-अलग वजन (1 किग्रा, 2 किग्रा, 3 किग्रा और 4 किग्रा) के साथ स्वैच्छिक कोहनी फ्लेक्सन और विस्तार, और b) सोलह स्वस्थ और सत्रह पोस्ट-स्ट्रोक विषयों में तीन अलग-अलग विद्युत उत्तेजना पैटर्न (अनुकूलित आयताकार, समलम्बाकार और मांसपेशी तालमेल-आधारित) के तहत FES प्रेरित कोहनी फ्लेक्सन पर किया गया है।

MEFFNet के एक संस्करण, जिसे पूर्व प्रशिक्षित (प्रीट्रेन्ड) MEFFNet नाम दिया गया है, को साठ हजार सिंथेटिक समय श्रृंखला के डेटासेट पर प्रशिक्षित किया गया ताकि थकान के मायोइलेक्ट्रिक सूचकांकों की वास्तविक समय श्रृंखला पर इसके सीखने को स्थानांतरित किया जा सके। पूर्व-प्रशिक्षित MEFFNet स्वैच्छिक संकुचन में $15.99 \pm 6.48\%$ और FES-प्रेरित संकुचन में $11.93 \pm 4.77\%$ की औसत निरपेक्ष प्रतिशत त्रुटि के साथ भविष्य में 22.62 सेकंड (60 टाइमस्टेप्स) तक का पूर्वानुमान लगा सकता है, जो MEFFNet और विचाराधीन अन्य मॉडलों से काफी बेहतर प्रदर्शन करता है ($p < 0.05$, एकतरफा दोहराया माप एनोवा/ANOVA)। परिणाम पूर्वानुमान रणनीतियों और सिस्टम प्रतिक्रियाशीलता को बढ़ाने के लिए पहनने योग्य तकनीक, कृत्रिम अंग या प्रोस्थेटिक्स, रोबोटिक्स और विद्युत उत्तेजना उपकरणों के साथ प्रस्तावित मॉडल को संयोजित करने का सुझाव देते हैं।

उपरोक्त कार्य ने दिखाया कि समय श्रृंखला पूर्वानुमान में ट्रांसफर लर्निंग के जरिये पहनने योग्य सेंसर के भविष्यवाणियों को बेहतर बनाया जा सकता है।

यह थीसिस मांसपेशी तालमेल-आधारित FES प्रणाली के विकास की खोज करती है, जिसकी परिकल्पना मोटर कार्यों को करने में शामिल प्राकृतिक तंत्रों का लाभ उठाकर विद्युत उत्तेजना-प्रेरित थकान को कम करने के लिए की गई है। मांसपेशी थकान में कमी के लिए बायोमिमेटिक विद्युत उत्तेजना टेम्पलेट का चयन करने के इस ज्ञान पर निर्माण करते हुए, sEMG संकेतों का उपयोग करके मांसपेशी थकान के मायोइलेक्ट्रिक सूचकांकों की भविष्यवाणी करने के लिए एक डीप लर्निंग फ्रेमवर्क पेश किया गया था, जिसका उपयोग वास्तविक समय में निगरानी और अनुकूली नियंत्रण को सुविधाजनक बनाने के लिए किया जा सकता है, जिससे विद्युत उत्तेजना प्रेरित मांसपेशी थकान को कम करने की रणनीतियों को आगे बढ़ाया जा सकता है। इस थीसिस में प्रस्तुत शोध विधियाँ और परिणाम शोधकर्ताओं और फिजियोथेरेपिस्टों को प्रभावी विद्युत उत्तेजना पैटर्न का चयन करने के लिए मूल्यवान तकनीकें प्रदान करते हैं, जिससे स्ट्रोक के बाद पुनर्वास लाभों को अधिकतम किया जा सकता है। इसके अतिरिक्त, थकान संकेतकों का पूर्वानुमान लगाने की क्षमता विद्युत उत्तेजना मापदंडों के वास्तविक समय संशोधनों को सूचित कर सकती है। ये प्रगति न केवल FES की प्रभावशीलता को बढ़ाती है, बल्कि भविष्य में वास्तविक समय में थकान प्रबंधन के लिए आधार भी तैयार करती है, जिससे रोगी के परिणामों को अनुकूलित करने के लिए चल रहे FES सत्रों में गतिशील समायोजन का अवसर मिलता है। ये निष्कर्ष स्ट्रोक के बाद के रोगियों के लिए FES थेरेपी में सुधार कर सकते हैं, जिससे तेजी से आरोग्य प्राप्ति या रिकवरी और अधिक स्वतंत्रता को बढ़ावा मिल सकता है।

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The MAA values of synergist muscles across all subjects under all weights were significantly different from that of flexor muscles and extensor muscles ($p < 0.05$, the Kruskal Wallis test, and for pair-wise comparisons, $p < 0.01$, Dunn Test Bonferroni Corrected).

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ABBREVIATIONS

ANOVA	Analysis Of Variance
ARIMA	Autoregressive Integrated Moving Average
ARV	Average Rectified Value
BB	Biceps Brachii
BCI	Brain Computer Interface
BiLSTM	Bidirectional Long Short-Term Memory
BP	Backpropagation
BR	Brachioradialis
CIMT	Constraint-Induced Movement Therapy
CMUAP	Compound Motor Unit Action Potential
CNN	Convolutional Neural Network
CNS	Central Nervous System
CWT	Continuous Wavelet Transform
EEG	Electroencephalography
eEMG	Evoked Electromyography (Context: FES)
EMD	Empirical Mode Decomposition
EMG	Electromyography
ES	Electrical Stimulation
ETS	Exponential Smoothing
FES	Functional Electrical Stimulation
FF	Fast-Twitch Fatigable
FFR	Fast-Twitch Fatigue-Resistant
FFT	Fast Fourier Transform
FM Score	Fugl Meyer Scores
GAN	Generative Adversarial Network
GBD	Global Burden of Diseases
ICA	Independent Component Analysis
IIR	Infinite Impulse Response
IMF	Intrinsic Mode Function
IMU	Inertial Measurement Unit
LSTM	Long Short-Term Memory

MAA	Mean Absolute Autocorrelation
MAPE	Mean Absolute Percentage Error
MAS	Modified Ashworth Scale
MAV	Mean Absolute Value
MDF	Median Frequency
MEFFNeT	Myoelectric Fatigue Forecasting Network
MNF	Mean Frequency
NARX-RNN	Nonlinear AutoRegressive with eXogenous inputs - Recurrent Neural Network
NLMS	Normalized Least Mean Squares
NNMF	Non-Negative Matrix Factorization
PCA	Principal Component Analysis
PTP	Peak-To-Peak (Context: Amplitude)
RCT	Randomized Clinical Trial
RMS	Root Mean Square
SCI	Spinal Cord Injury
SD	Standard Deviation
sEMG	Surface Electromyography
SFR	Slow-Twitch Fatigue Resistant
SNR	Signal to Noise Ratio
SSM	Similarity of the Synergy Matrix
SSV	Similarity of Synergy Vectors
TA	Tibialis Anterior
TIA	Transient Ischemic Attack
TMS	Transcranial Magnetic Stimulation
UE	Upper Extremity
USD	United States Dollar
VAF	Variance Accounted For
vEMG	Volitional EMG
VR	Virtual Reality