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AI-Powered Detection of Muscle Fatigue in Long-Duration Activities Using Surface EMG

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Abstract. Muscle fatigue is of great importance during any kind of physical activity, as it reduces the performance of the body part and, in extreme cases, can even cause harm to the individual. Surface electromyography (sEMG) has emerged as one of the most prevalent methods for assessing muscle state and fatigue-related changes. This paper suggests a deep learning-based approach to detect the onset of muscle fatigue caused by long-duration, low-intensity HCI tasks, namely, typing, gaming, and using a mouse for an extended period of time, which is not much talked about compared to high-intensity or athletic fatigue. The proposed method employs a CNN-LSTM model and physiologically meaningful time-frequency characteristics (RMS Amplitude, Zero Crossing Rate, and Median Frequency) to predict the occurrence of fatigue. A multistage signal-preprocessing chain, including a band-pass filter, full-wave rectification, RMS smoothing, and normalisation, is applied prior to classification. All experiments are conducted on the NinaPro DB2 public dataset to ensure reproducibility. Results from signal-level analysis revealed clear, nonstationary amplitude variations throughout the signal, in the form of sporadic high-amplitude events, which are attributed to motor unit recruitment during continuous muscle activation. This demonstrates the feasibility of the method and provides a basis for developing a portable muscle fatigue detection sensor.

Keywords: Surface Electromyography, muscle fatigue, deep learning, CNN-LSTM, human-computer interaction, wearable sensors.

1. INTRODUCTION

A. Motivation

With the advent of digitalization of work and recreation, there has been a marked increase in the amount of time individuals spend working in a repetitive and low energy manner. Examples of such behaviors include typing, playing games, and constant usage of a mouse. Despite their relative physical ease, these actions result in sustained muscle activity and subsequent fatigue, particularly in the forearm, wrist, and shoulder region. Prolonged fatigue can eventually result in physical discomfort and RSIs [1].

Muscle fatigue is commonly described as a gradual decline in a muscle's ability to generate force after prolonged use, and it is accompanied by physiological changes such as altered motor unit recruitment and reduced muscle fibre conduction velocity [2]. Surface electromyography (sEMG) offers a noninvasive way to observe these changes by measuring the electrical activity of skeletal muscles. Traditional sEMG fatigue analysis relies on manually extracted time- and frequency domain features such as root mean square (RMS) amplitude and median frequency shifts, both of which have shown strong relationships with fatigue progression [3]. However, most prior work targets high intensity or short duration activity performed by athletes or during rehabilitation, and depends on expensive medical grade equipment, leaving everyday HCI induced fatigue largely unaddressed [4].

B. Main Contributions

To address this gap, this paper makes the following contributions:

1) It targets gradual fatigue in long duration, low intensity HCI tasks, an under explored regime in which simple threshold based models are poorly suited [4].

2) The approach utilizes the hybrid CNN-LSTM model, integrating automatic feature learning along with physiologically meaningful features, such as RMS, Zero Crossing Rate, and Median Frequency, without compromising the power of deep learning techniques [5].

3) It develops and validates the complete preprocessing and analysis pipeline on the public NinaPro DB2 dataset, avoiding costly new data collection and enabling reproducible comparison [12].

4) It designs the framework with computational efficiency in mind so that it is suitable for future deployment on low cost wearable devices.

C. Research Objectives and Key Findings

The objectives of this study are: (i) to design a noise robust preprocessing pipeline for sEMG signals acquired in conditions representative of prolonged HCI; (ii) to extract interpretable fatigue related features and combine them with a CNN-LSTM architecture able to model both short term and long term signal behaviour; and (iii) to verify, on a public benchmark, whether fatigue related trends can be reliably observed in the resulting feature representations.

The key findings are that the RMS amplitude envelope extracted from NinaPro DB2 is strongly nonstationary, exhibiting contraction by contraction fluctuation together with intermittent high amplitude episodes that are consistent with changing motor unit recruitment during sustained activity [2], [7], and that even simple time domain features capture these activation changes without complex modelling. These observations confirm the feasibility of the proposed framework and motivate its full training and deployment as future work.

D. Organization of the Paper

The rest of the paper proceeds as follows. Section II provides a literature review on sEMG based fatigue estimation techniques. Section III discusses the proposed data acquisition approach along with the experimental setup. Section IV explains the preprocessing approach and feature extraction process with the governing equations involved. Section V introduces the deep neural network framework and its training procedure. Section VI shows the results along with a comparative analysis. Sections VII, VIII, and IX provide the discussion, limitations, and conclusion, respectively.

2. RELATED WORK

Detection of muscle fatigue via sEMG was researched extensively in the field of sports sciences, ergonomics, and clinical applications in the past decades. Early works were mainly interested in studying the underlying mechanisms of fatigue and discovering meaningful signal signatures. De Luca [2] and Merletti and Parker [1] found out that muscle fatigue is commonly characterized by increasing amplitude of the EMG signal and progressive lowering of signal spectrum due to reduced motor fiber conduction velocities and specific motor unit activity. Neural control strategy can also be detected from surface EMG which provides a theoretical framework for designing amplitude and frequency based indicators of fatigue [7].

Existing methods of fatigue detection are mostly based on handcrafting features. Typical time domain features include root mean square (RMS), mean absolute value (MAV), and integrated EMG (IEMG). Commonly used frequency domain features include median frequency (MDF) and mean frequency (MNF) [3]. Clancy, Bouchard, and Rancourt [8] provided the means for making amplitude estimate robust under nonstationary muscle fatigue condition. These features are attractive because they are simple to compute and physiologically meaningful, but their reliability can be affected by intersubject variability, electrode placement, and task type [3].

To mitigate these problems, machine learning algorithms including SVM, KNN, and decision tree classifications have been employed for EMG features with limited success [3]. Nonetheless, these approaches continue to be highly reliant on the extraction of specific features, hence failing to account for the differences between users and tasks.

Deep learning techniques can also be considered a better option since these are capable of identifying features on the basis of the input data or its transformation. It has been seen that CNNs have achieved success when used for gestures recognition and muscle state detection, using the sEMG signal. CNNs are particularly successful in extracting spatial and local temporal relationships present within multichannel biosignals [10]. Long range temporal dependency can be captured by recurrent models, in particular LSTMs [6]. The nature of fatigue is quite consistent with capturing long term dependency, as fatigue occurs gradually; hence, Wang et al. [4] state that fatigue recognition based on LSTM is superior to other classifiers like CNN and SVM for EMG based fatigue recognition.

Hybrid architectures that combine CNN and LSTM layers have therefore become increasingly popular: convolutional layers extract discriminative features while recurrent layers model their temporal evolution, yielding higher accuracy for fatigue classification and good handling of nonstationary signals [4], [5]. Related work on deep learning for sensor and wearable based human activity and fatigue monitoring [9], [11] further supports the suitability of such models for continuous, real world monitoring.

Despite this progress, most studies still concentrate on fatigue induced by resistance training, rehabilitation, or laboratory contractions [4]. Relatively few works address fatigue caused by long duration, low intensity activities such as typing or gaming, where the physiological load accumulates slowly, and most rely on expensive laboratory grade equipment. The present study targets this gap by addressing HCI induced fatigue with a hybrid CNN-LSTM model validated on the publicly available NinaPro DB2 dataset rather than newly recorded data.

3. PROPOSED DATA ACQUISITION AND EXPERIMENTAL PROTOCOL

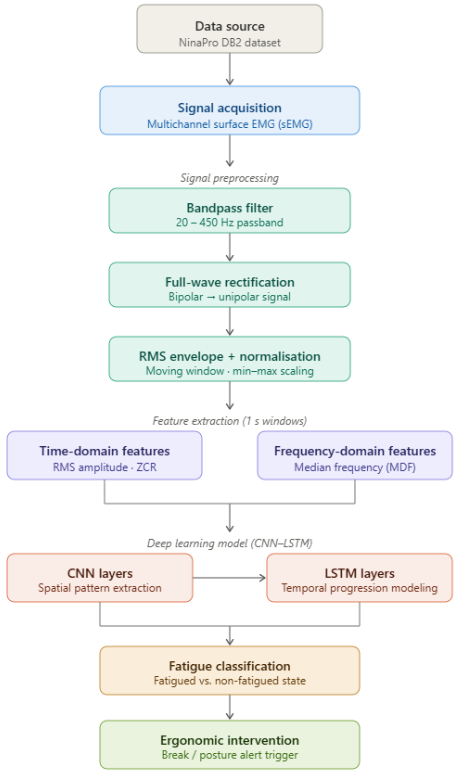

Fig. 1. Block diagram of the proposed sEMG based muscle fatigue detection pipeline

Architecture of the proposed real time muscle fatigue detection system is explained in this section and includes integration of surface EMG and inertial sensors. In particular, the goal of the proposed system design is to achieve synchronization of both data streams in order to interpret the muscle activity under performance of sustained tasks. Combining these types of signals will shed more light on dynamics of fatigue progression and their association with certain body movement. General outline of the workflow is presented in Fig. 1. As far as our research concerns, in the validation phase, we use sEMG signals obtained from the publicly available NinaPro DB2 database, instead of using sensor data [12]. It includes several channels of high quality sEMG data and allows to validate developed preprocessing techniques and to observe effects of fatigue on muscles' activity.

4. SIGNAL PREPROCESSING AND FEATURE REPRESENTATION

Raw EMG is inherently noisy and time varying because of motion artefacts, electrode drift, skin impedance variation, and electromagnetic interference, which make the true muscle signal hard to isolate. Appropriate preprocessing is therefore required to suppress unwanted noise without distorting the fatigue related characteristics of the signal [1]. In this study a multistage pipeline was applied to signals extracted from NinaPro DB2 before feature extraction.

A. Filtering and Rectification

A fourth order Butterworth bandpass filter with cutoff frequencies of 20 Hz and 450 Hz was first applied. This band retains the dominant spectral content of muscle activity while removing low frequency motion components and high frequency noise [2]. Full wave rectification was then applied to convert the bipolar EMG into a unipolar signal, which makes amplitude changes easier to analyse. Fig. 2 contrasts a raw segment with its bandpass filtered counterpart.

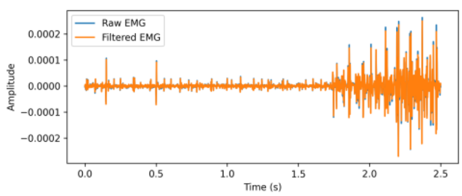

Fig. 2. Raw and bandpass filtered surface EMG signal from the NinaPro DB2 dataset.

B. Smoothing and Normalization

To obtain a smooth representation of muscle activity, a moving window RMS was computed from the rectified signal. For a window of Nsamples, the RMS amplitude is defined in (1):

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} \qquad (1)$$

The RMS operation in (1) produces a distinct signal envelope that more clearly represents variations in muscle activation, and RMS amplitude is an effective measure of activation intensity that correlates with fatigue related change during prolonged activity [3], [8]. After feature extraction, all values were rescaled to a common range, as given in (2):

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (2)$$

C. Feature Representation

For each one second EMG segment, both time- and frequency domain features were computed. The time domain set comprises RMS amplitude (1), mean absolute value (MAV), and zero crossing rate (ZCR). MAV, defined in (3), measures average activation level, while ZCR, defined in (4), reflects how often the signal changes polarity and therefore indicates frequency related change during contraction:

$$\mathrm{MAV} = \frac{1}{N}\sum_{n=1}^{N} | x_n | \qquad (3)$$

$$\mathrm{ZCR} = \sum_{n=1}^{N-1} g\,(x_n, x_{n+1}),\ g = \begin{cases} 1, & \text{if } x_n x_{n+1} < 0 \\ 0, & \text{otherwise} \end{cases} \qquad (4)$$

From the frequency domain, the median frequency (MDF) is used because it is a well established fatigue indicator: as fatigue progresses, the power spectrum shifts toward lower frequencies and the MDF decreases [1], [2]. The MDF is the frequency that divides the power spectral density $P(f)$into two equal energy halves, as defined in (5):

$$\int_0^{f_{med}} P\,(f)\,df = \int_{f_{med}}^{\infty} P\,(f)\,df = \frac{1}{2}\int_0^{\infty} P\,(f)\,df \qquad (5)$$

Although deep models can learn features directly from raw signals, adding these physiologically interpretable descriptors (1)–(5) can improve performance when the dataset is small [4]. The resulting feature vectors were fed into the neural network so that it could learn fine grained changes while retaining known physiological indicators of fatigue. The amplitude and frequency changes observed during this process were consistent with previously reported neuromuscular adaptations during fatigue [7].

5. DEEP LEARNING ARCHITECTURE AND TRAINING PROCEDURE

A. Hybrid CNN-LSTM Architecture

Fatigue onset is gradual in nature; thus, the evolution of fatigue will show up through modifications in the sEMG pattern at both short and long periods. Hence, an appropriate model should be capable of extracting short and long-term patterns in addition to other features of the signal. The architecture under consideration is a combination of convolutional layers and LSTM layers (CNN-LSTM). It is powerful enough for extracting powerful features along with modeling sequences. Firstly, the feature vectors in the form of time series will be transformed using convolutional layers in order to detect certain patterns from the signal, which describe the activity of the muscles and the state of fatigue. CNN is a proper choice for handling multichannel signals as well as biosignals since it extracts discriminative features without being dependent entirely on predefined features [10]. Some filters can be used for reducing the effect of noise and intersubject variability. Pooling layers will reduce the size of the signal.

In the next stage, these extracted feature maps will be forwarded to LSTM layers that analyze their development over sequential intervals. Since LSTM units maintain information over time [6], they are ideal in capturing progressive fatigue states.

B. Implementation Details

The training and testing process was done using standard deep learning packages on a desktop computer. The model design was based on the concept of making a design that is practical in real time, meaning that the design will be made in such a way as to maintain simplicity, making it useful when implemented in fatigue detection wearables.

6. RESULTS AND OBSERVATIONS

A visual analysis of the EMG features obtained from NinaPro DB2 reveals structure that can be linked to muscle activation and fatigue. As shown in Fig. 3, the RMS amplitude is strongly nonstationary: it fluctuates from window to window in line with the repeated contraction protocol of the dataset, and several episodes of clearly elevated amplitude appear over the course of the recording (for example around windows 2700–3100 and beyond window 8500). Physiologically, such bursts of increased RMS are consistent with greater neural drive and additional motor unit recruitment during the more demanding or later contractions [2], [7]. Rather than a single monotonic ramp, the envelope therefore shows intermittent high amplitude episodes superimposed on the contraction by contraction variation, indicating that the temporal evolution of the surface EMG still carries usable information about changing muscle activation and the onset of fatigue.

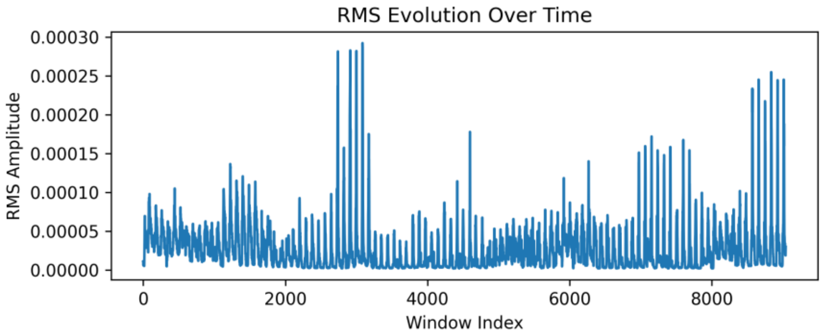

Fig. 3. Evolution of RMS amplitude across analysis windows for sEMG signals from the NinaPro DB2 dataset.

Two observations follow. First, even simple time domain features such as RMS reflect fatigue related change without complex signal modelling, which is attractive for lightweight, real time implementations. Second, although no quantitative classification results were produced in this study, since model training and evaluation are deferred to future work, the consistency of these amplitude variations with established muscle activation physiology supports the validity of the chosen feature set and motivates full evaluation of the architecture. The feature representation therefore provides a sound input for the automated CNN-LSTM classifier described in Section V.

A comparative quantitative analysis may not be within the scope of this preliminary investigation; however, it will be possible to analyze the proposed model qualitatively in relation to some alternatives. Handcrafted feature based classifiers like SVM, KNN, and decision trees offer a good point of comparison, but are limited by requiring manual construction of the features, which cannot model temporal dependency. Convolutional Neural Networks (CNN) offer an improvement in that they are capable of modeling both spatial and local patterns, whereas Long Short Term Memory (LSTM) networks are designed to model the temporal dependency of data. The CNN-LSTM approach used in this case exploits these two strengths simultaneously; it combines physiologically meaningful features with machine learning techniques and studies the temporal dependency of fatigue.

7. DISCUSSION

It can be seen from the results that the use of surface EMG analysis can provide valuable information on changes in the activity of muscles undergoing prolonged action. As shown above, window to window variations in the signal as well as high amplitude peaks appearing intermittently in RMS amplitude measured using NinaPro DB2 allow us to identify fatigue related changes using sEMG data. In terms of practical application, the main advantage of the approach presented in this paper lies in its computational efficiency. Despite a publicly available benchmark being used in this paper, the system was developed considering the limitations imposed by the future fatigue monitoring device. It appears that the use of CNN and LSTM layers is very suitable for solving the stated problem. Fatigue development occurs gradually rather than instantaneously, which allows to use CNN layers for extracting useful features of the EMG signal along with applying LSTM layers to analyze its temporal dynamics, something already proven effective for analyzing EMG signals before [4], [5].

8. LIMITATIONS

Several limitations of the present work should be acknowledged. First, the study did not involve live data acquisition or testing on realistic HCI tasks; it relied entirely on the publicly available NinaPro DB2 dataset, which, although high quality, was not collected specifically for prolonged low intensity computer use. Second, full model training, classification, and quantitative evaluation were not performed, so the reported findings are based on signal- and feature level trends rather than measured classification accuracy. Third, fatigue behaviour can vary considerably with the individual, the type of fatigue, and the muscle group involved, and these intersubject and task specific variations were not yet characterized. Addressing these points, through real time data collection, complete model training, and subject independent validation, forms the basis of the planned future work.

9. CONCLUSION

This work presented a deep learning approach for muscle fatigue detection from surface EMG, focusing on the under explored case of gradual fatigue during long duration, low intensity human computer interaction. By combining convolutional and recurrent layers, the CNN-LSTM architecture is able to analyse both the short term structure and the longer term temporal evolution of fatigue, while interpretable features (RMS, MAV, ZCR, and MDF) keep the representation physiologically grounded. A multistage preprocessing pipeline of band pass filtering, full wave rectification, RMS smoothing, and normalization was used to suppress noise while preserving the signal characteristics that carry information about fatigue.

The analysis of benchmark EMG signals from NinaPro DB2 showed a nonstationary RMS amplitude pattern, including high amplitude periods, which is in line with the theory of varying motor unit recruitment while maintaining constant activity [2], [7]. It is encouraging to observe that such patterns can be identified even when analysing simple time domain measures, as it implies that some meaningful information concerning fatigue is still available even when avoiding complex models, making fatigue detection feasible through low complexity algorithms. These findings prove the viability of surface EMG combined with proper signal processing algorithms as tools for real life fatigue assessment. With regard to practical applications, the importance of such fatigue detector should not be overlooked. As a tool to monitor forearm, wrist and shoulder muscle activity during extended computer operation, it can help identify cases where a break, change of position or relaxation of the muscles is required in order to prevent pain or development of a repetitive strain injury. Being designed in such a way that makes it lightweight and fast, the proposed framework is ready to be used as a foundation of a fatigue detection system implemented in a wearable device.

In spite of this, the study clearly had limitations as discussed in Section VIII. It lacked live data collection, no complete training of the model was done, and classification accuracy could thus not be evaluated, hence making the comparisons with other models qualitative and not quantifiable. In subsequent research, these limitations are expected to be sorted out through the collection of real time EMG and inertial IMU data using wearable sensors. In addition, there will be comprehensive training and evaluation of the suggested model. Realistic experimentations on several subjects will be conducted with the aim of establishing the generalization capacity of the model. Other areas that need exploration include the role played by certain parameters like the individual subject, muscles targeted, and activities carried out in influencing fatigue behavior. This study forms an initial step towards further developing muscle fatigue monitoring system in the domain of human computer interaction [6], [9], [11].

Conflict of Interest

The authors declare no conflicts of interest regarding the current research.

References

[1] R. Merletti and P. A. Parker, Eds., Electromyography: Physiology, Engineering, and Non-invasive Applications. Hoboken, NJ, USA: Wiley–IEEE Press, 2004. ISBN 978-0-471-67580-8.
[2] C. J. De Luca, "The use of surface electromyography in biomechanics," J. Appl. Biomech., vol. 13, no. 2, pp. 135–163, 1997. doi: 10.1123/jab.13.2.135.
[3] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for EMG signal classification," Expert Syst. Appl., vol. 39, no. 8, pp. 7420–7431, 2012. doi: 10.1016/j.eswa.2012.01.102.

[4] J. Wang, S. Sun, and Y. Sun, "A muscle fatigue classification model based on LSTM and improved wavelet packet threshold," Sensors, vol. 21, no. 19, art. no. 6369, 2021. doi: 10.3390/s21196369.
[5] D. Bai, T. Liu, X. Han, and H. Yi, "Application research on optimization algorithm of sEMG gesture recognition based on light CNN+LSTM model," Cyborg Bionic Syst., vol. 2021, art. no. 9794610, 2021. doi: 10.34133/2021/9794610.
[6] S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural Comput., vol. 9, no. 8, pp. 1735–1780, 1997. doi: 10.1162/neco.1997.9.8.1735.
[7] D. Farina, R. Merletti, and R. M. Enoka, "The extraction of neural strategies from the surface EMG," J. Appl. Physiol., vol. 96, no. 4, pp. 1486–1495, 2004. doi: 10.1152/japplphysiol.01070.2003.
[8] E. A. Clancy, S. Bouchard, and D. Rancourt, "Estimation and application of EMG amplitude during dynamic contractions," IEEE Eng. Med. Biol. Mag., vol. 20, no. 6, pp. 47–54, 2001. doi: 10.1109/51.982275.
[9] J. Wang, Y. Chen, S. Hao, X. Peng, and L. Hu, "Deep learning for sensor-based activity recognition: A survey," Pattern Recognit. Lett., vol. 119, pp. 3–11, 2019. doi: 10.1016/j.patrec.2018.02.010.
[10] J. Yang, M. N. Nguyen, P. P. San, X. Li, and S. Krishnaswamy, "Deep convolutional neural networks on multichannel time series for human-activity recognition," in Proc. 24th Int. Joint Conf. Artif. Intell. (IJCAI), Buenos Aires, Argentina, 2015, pp. 3995–4001.
[11] N. R. Adão Martins, S. Annaheim, C. M. Spengler, and R. M. Rossi, "Fatigue monitoring through wearables: A state-of-the-art review," Front. Physiol., vol. 12, art. no. 790292, 2021. doi: 10.3389/fphys.2021.790292.
[12] M. Atzori, A. Gijsberts, C. Castellini, B. Caputo, A.-G. Hager, S. Elsig, G. Giatsidis, F. Bassetto, and H. Müller, "Electromyography data for non-invasive naturally-controlled robotic hand prostheses," Sci. Data, vol. 1, art. no. 140053, 2014. doi: 10.1038/sdata.2014.53.