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Soft Physiology Sensors and Machine Learning to Enhance Spinal Cord Injury and Stroke Rehabilitation Outcomes in Home Settings

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ABSTRACT

This paper presents the design and fabrication of a textile-based soft Electromyography (EMG) sensor and machine-learning-based methods to detect muscle spasticity. The textile EMG sensor is flexible, foldable, stretchable, washable for multiple times, and easily customizable to meet the heterogeneous needs of SCI individuals. The machine learning algorithms that can estimate the muscle status and the performance of functional ADLs by classification of function ADLs and the detection of muscle spasticity. The soft textronic sensors, its intelligent machine learning algorithms, and biofeedback-based rehabilitation has the potential to enable home-based rehabilitation and encourage more manipulation for function ADLs and independence in SCI and stroke individuals.

INTRODUCTION

High-dosage rehabilitation is beneficial for functional recovery, which encourages the spinal cord injury (SCI) patients to use their affected limbs as much as possible. Rehabilitation in home settings could provide high-dosage rehabilitation of activity of daily living (ADL). However, SCI and stroke individuals typically suffer from spasticity, which significantly limits the movement control and quality of their daily lives thus the dosage. Hence, a system that can monitor the physiological condition and measure spasticity in their daily life is desirable. The purpose of this study is to customize the soft fabric sensors to maximize the comfort, measure muscle activities for SCI individuals, and to develop machine-learning-based algorithms to detect muscle spasticity.

METHODS

The wearable technology has numerous fields of applications capturing and emphasizing several key trends such as sports and leisure, healthcare, apparel, fashion, and consumer electronics. However, it is still rarely adopted by individuals with SCI or stroke as those devices are typically rigid, heavy, bulky and uncomfortable. Our soft sensing fabric [1-5] is substantially different from other solutions because it is made of textile that is flexible, foldable, stretchable, washable for multiple times. Unlike rigid wearable device and other health monitor devices (e.g. Yamaguchi University belt-type cardiorespiratory signal sensor [6], Northwestern University wearable EMG sensors [7], Zio patch [8]), soft sensing fabric interfaces to the body via unobtrusive, conformal, and compliant textile material and also measure the bio-potential signal (ECG and respiratory signal), motion information (accelerate, angular velocity), activities detection (walking, running, climbing, and falling), and biofeedback (falling alarm, heart rate, heart rate variability, respiratory rate).

We have developed a soft wearable sensor [2-6] to measure EMG signals. Then we collected data from one SCI subject and extracted the key features. We then performed feature selection and trained a linear model and compared it with a recently developed model [9].
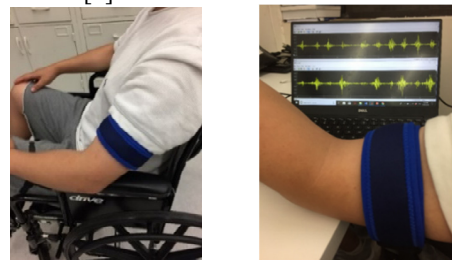

Fig. 1. (Left) Demonstration of the soft fabric sensor in an SCI subject. (Right) The real-time recording for the EMG signal of biceps and triceps.
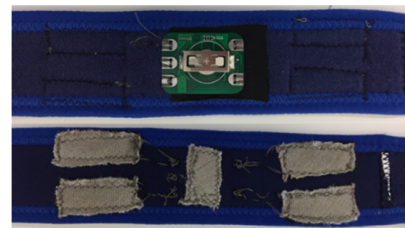

Fig. 2. (Top) Microcontroller integrated into the textile sensor for EMG measurement and wireless transmission. (Bottom) The configuration of

fabric EMGs: the EMG sensors have five electrodes, two pairs of electrodes for measuring biceps and triceps muscle signal separately, another one electrode as a reference.

Spasticity is the symptom of abnormal muscle contraction due to neurological disorders, such as spinal cord injury, stroke, multiple sclerosis, and cerebral palsy. The EMG signal of spasticity from our data set is shown as Fig. 3 (a). Assessing the progression of spasticity during clinical interventions and at home is key to rehabilitation efficacy and care management [8].

In order to discriminate the spasticity in the subjects with SCI, we collected data from one SCI subject and compared the 15 features from [9]. The data extracted procedure is similar to the method of [9] and is shown in Fig. 3 (b). The raw EMG data is firstly split into windows with the size of 0.5s and the slide of 0.1s. For each window, the statistics form the features of each data point, while whether the subject has spasticity during this period forms the label of each data point. To compare our model with the model in [9], 2 sets of features are extracted. One set contains the same 15 features as [9], while the other one contains only the mean of absolute value (MAV) and the root-mean-square value (RMS).
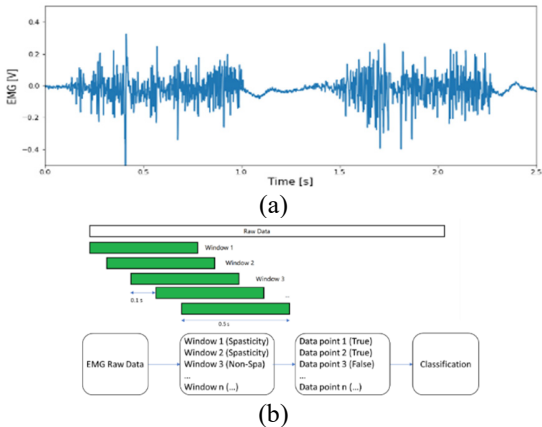

(a)

(b)

Fig 3.   (a) The EMG signal of muscle with spasticity. (b) The samples in 0.5 second are used as the extracted data set and the interval of each extracted data is 0.1 second.

The whole dataset used in this research consists of two parts: one is the data gathered from our own EMG sensor, and another is the dataset in [9]. These two datasets are represented as Our Data and Northwestern University (NWU) Data respectively in the following part. Both datasets use EMG signals from Gastrocnemius. Two models are trained: one model is trained on our dataset by a Logistic Regression method (linear model), while the other one is from [9]. These two models are represented as Our Model and NWU Model respectively. Both models are tested on two datasets for comparing purpose.

RESULTS

Based on the data analysis, it is observed that the two most important features are MAV and RMS and that the spasticity have higher power density spectrum (PDS) than normal muscle contraction in the lower frequency between 0~40 Hz. In Fig. 4

(a), the red points represent spasticity, the blue points represent voluntary contraction, and it is straightforward to separate the two groups by a green line. We compared the receiver operating characteristic (ROC) curve between our model and NWU model [9]. It demonstrates that our 2-features model has similar performance on both Our Data and NWU Data without significant loss of accuracy shown as in Fig. 4 (b), while NWU Model has a significant loss in accuracy on Our Data, which indicates that our model is more generic in different data sets, sensors, and subjects. The loss of robustness of NWU's high-dimension model could be caused by the systematic variances between the sensors and subjects, which change the properties of some features.
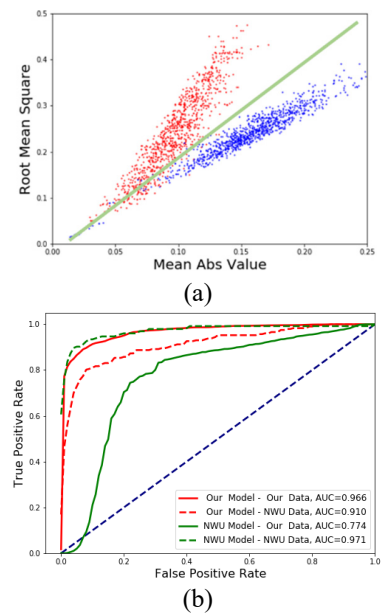

(a)

(b)

Fig 4.   (a) Extracted data points of EMGs: The Mean-Absolute-Value (MAV) and Root-Mean-Square (RMS) based on 0.5s window size. The red cluster represents spasticity, while the blue cluster represents voluntary contraction. The green line is the boundary of our linear classifier. (b) ROC to compare different models: NWU's 15-features model has better performance on Northwestern University dataset, with significantly worse performance on our dataset. Our 2-features model has similar performance on both NWU's and our datasets without loss of accuracy, which indicates that our model is more generic in different data set, sensors, and subjects.

CONCLUSIONS

Our soft EMG sensor is more conformal, comfortable and durable than conventional rigid EMG sensors while it demonstrates similar accuracy with those golden standard EMG sensors. Since we only deploy two features and the model is linear, which means our model only uses a small amount of space and calculation resources, our model can be easily implemented and used to detect spasticity in an embedded system. The ROC result indicates that our model is more generic across different dataset, sensors, and subjects. The future work will focus on system evaluation with standard EMG sensors and integration

with a soft robotic glove [8] for assistance and rehabilitation in the home and community settings.

ACKNOWLEDGMENTS

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