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**CMU-RI-TR-20-07**

**March 2020**

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# Toward automated interpretation of electromyography for intraoperative neurophysiological monitoring using machine learning

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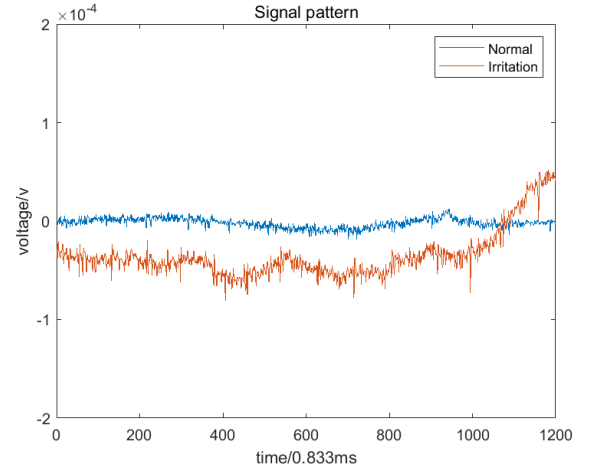
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## ABSTRACT

Intraoperative neurophysiological monitoring is used during neurosurgery to assess the functional integrity of nerves and alert the surgeon to prevent damage. In current clinical IONM, the neurophysiological data are interpreted in real time by a specialist. This processing by humans is subjective and introduces inter-subject variability into the process. In order to standardize this process and reduce cognitive load on human users, this paper presents a preliminary investigation of the use of machine learning techniques for automated detection of nerve irritation during neurosurgery.

## INTRODUCTION

Intraoperative neurophysiological monitoring (IONM) is used during certain high-risk surgeries to assess the functional integrity of nerves and alert the surgeon to prevent damage. In current clinical IONM, the neurophysiological data are interpreted in real time by a physician who then reports abnormal situations to the surgical team during operation [1]. However, there are two main problems in the practice of IONM. Firstly, evaluation of signal content is subjective; differences in training cause differences in human determination of incipient damage and resulting adjustment of dissection technique. Secondly, during surgical procedures, latency in verbal communication between surgeon and the neurophysiologist may exacerbate injury due to unpredictably rapid changes. To address the former, we applied a hybrid CNN-RNN model to automatically classify abnormal surface electromyography (EMG) pattern to provide real-time alarming. In the long term, we hope to address the latter by including such monitoring with the control system of surgical robotic systems as an intraoperative safety check to which the control system can respond automatically.



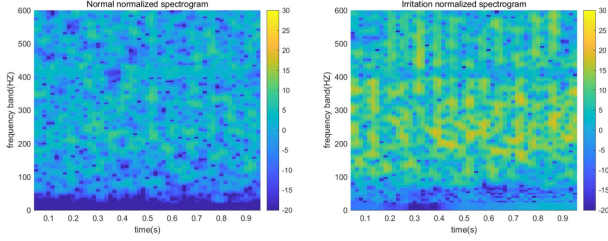
**Fig. 1:** Normal EMG activity and irritation EMG activity

## MATERIALS AND METHODS

### Data acquisition and labeling

The data we use is single-channel unstimulated (continuous) EMG and stimulated EMG in thyroid surgery from one patient provided by Computational Diagnostics Inc. under a board-approved protocol. Data were recorded for 6547 s at 1200 Hz sampling. Recorded data were separated into epochs of 1 s. Neurophysiologists labeled data epoch by epoch according to significance on clinical setting and classified them two main patterns as shown in Fig.1:

- *Irritation Activity* is characterized by continuous irregular EMG activity that is composed of numerous overlapping components. Amplitudes are distributed randomly around the baseline, ranging from 0.02 to more than 5 mV. This represents 624 epochs of the dataset. This activity should be brought to the attention of the surgeon [2].



**Fig. 2:** Normalized spectrograms corresponding to normal activity (left) and irritation activity (right) from Fig.1.

- *Normal Activity* contains all activities with no clinical significance including both quiet EMG free-running signal and evoked EMG signal caused by extraneous activity (such as artifacts resulting from electrocautery, ultrasonic devices, movement of metal instruments in the wound, and other from unknown sources). Evoked EMG, muscle activity and artifacts can be classified as normal free-running EMG activity.

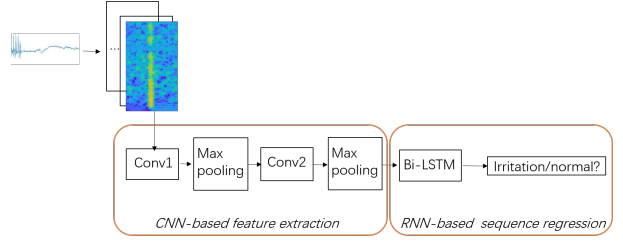
There exist also some epochs that exhibit clinically significant short-term "burst" activity, but these are beyond the scope of the present project and are not considered here.

### Data Normalization

In general, in EMG pattern recognition preprocessing, artifacts or other large signal changes are filtered out first [3]. However, this approach is less satisfactory in this application: artifacts sometimes are superimposed on irritation activity, so this might change the waveform to be analyzed. To deal with those problems, we normalize signals before classification. Firstly, we apply Short-time Fourier Transform (STFT) with sliding window size of 100 and 80% overlap between windows to get frequency band power density distribution for every sliding window. Then we use the mean and standard derivation of power density for every frequency band in the first 100 epochs to normalize frequency band power density of all subsequent sliding windows (the first 100 epochs are recorded before surgical intervention begins). Example spectrograms for normalized irritation and normal signal are shown in Fig.2.

### Hybrid CNN-RNN model

We built a hybrid CNN-RNN model which can effectively capture spatiotemporal information from surface EMG. The architecture for the proposed model is shown in Fig. 3. The convolution network (CNN) is applied as a feature extractor to transform normalized sequences into spatiotemporal feature vectors. The CNN model consists of two convolutional layers using 64 kernels with kernel size of 3 and two maxpooling layers with kernel size of 3. The recurrent neural network (RNN) encodes contextual information of temporal sequence [4]. Here we use



**Fig. 3:** Architecture for hybrid CNN-RNN model

a one-layer bidirectional long short-term memory (LSTM) with 256 hidden units to extract the time relationship between feature sequences.

In the training process, irritation activity is labeled by neurophysiologists and artifact is labeled by threshold method to recognize outliers. If the average normalized power density is larger than the threshold in a sliding window, the epoch is labeled as containing artifact.

We evaluated different values (5, 10, and 15 dB) as thresholds for recognition of artifacts (e.g., motion artifact). The threshold is used to avoid mistaking such content as irritation. We used 80% of the dataset for training and 20% for testing. The proposed neural network is trained on a graphics processing unit with learning rate of 0.01 and batch size of 64.

### RESULTS

Accuracy, sensitivity and specificity are used to evaluate the model under different threshold values for artifact. The table below presents the results.

Threshold(dB)	Accuracy	Sensitivity	Specificity
5	94.6%	96.0%	94.4%
10	98.4%	97.6%	98.5%
15	98.2%	94.4%	98.6%

### DISCUSSION

In this paper, we proposed a method for automatic detection of nerve irritation in IONM free-running EMG signals, which can be used as an alarm system during operation. The result shows relatively high detection accuracy with respect to human evaluation. In the future, this information can also be used as input to surgical robotic systems, to inform such systems that force or strain applied to tissue may need to be reduced.

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