**Studies on the usefulness of applying deep learning to interpreting EMG waveforms**

**Introduction**

Electromyography (EMG) is a electrophysiologic test that records electrical activity generated during muscle contraction controlled by nervous system. It is implemented to identify disorders of the nervous system or muscles according to abnormalities in EMG signals that reflect the anatomical and physiological characteristics of the nervous system and muscles. It is used as one of clues for diagnosing neurological or muscle diseases according to the characteristics of motor unit action potentials (MUAPs) among EMG signals. Typical neurogenic MUAPs seen in neurological diseases are known to have large amplitude, long duration, reduced recruitment, and reduced interference patterns. Interference is known to be small. pattern.

Electrophysiologic examination, including needle electromyography (EMG), nerve conduction studies, is obtained electrical signals from nerves, muscles and neuromuscular junctions, and is used to identifying any abnormalities in neuromuscular system, helping to estimate the location and extent of lesions. In case of patients with disorders of nerves, muscles, EMG shows waveforms made by damaged muscles or nerves including abnormal spontaneous potentials or action potentials generated by damaged muscles associated with nerve or muscle disorder. The diagnostic usefulness of electromyography for identifying peripheral neuropathy and myopathy has been suggested in previous studies. (1-7)

Previous studies have been reported that the accuracy of electromyography in patients with radiculopathy, the sensitivity was 36-64%, specificity 54-58%, inter-rater reliability was about 60-90% which is different according to type of abnormality.(1, 4, 6, 8-14) To recognize abnormalities of EMG waveform accurately, considerable time and efforts are needed. For diagnosing neuropathy and myopathy, higher accuracy of electromyography is required, and objective interpretation is required by decreasing the discrepancy between raters. As the importance and frequency of EMG, the workload of physicians and time taken for EMG get increased. This hardship might be alleviated by automated algorithms such as deep learning algorithms which assist physicians’ interpretations.

Recently, deep learning has been used to analyzing big data in many field, and it is also applied to clinical data including waveform, time series data. Recent development of deep learning technologies leads to gesture recognition based on EMG, assisting interpretation of electrocardiography and electroencephalography. Convolutional neural network, one kind of deep learning techniques, has applied to analyzing time series data and waveform data such as electrocardiography, electroencephalography. As a result of the study of reading the results of electrocardiography and electroencephalography using deep learning, the accuracy was similar to or superior to that of medical students or residents, and detect nonobvious abnormalities easily overlooked.(15) To our knowledge, previous studies on analyzing volitional EMG data have rarely been reported.

In order to increase the accuracy of electromyography, we applied deep learning to interpreting the EMG waveforms, and assess the accuracy of machine learning based-EMG interpretation and compare the results done by physicians’. We retrospectively reviewed EMG waveforms, which were examined in patients with neuropathy or myopathy or normal, analyzed those by using convolutional neural network built-in Python.

**Methods and materials**

**Data acquisition and preparation**

The data analyzed in this article were from the Seoul National University Hospital database that includes electromyography data of 58 subjects, visited Seoul National University Hospital from Jun, 2015 to Jul, 2020 and divided into 3 datasets of neuropathy, myopathy and normal according to EMG waveforms characteristics which were neurogenic potentials or myopathic potentials or not. The criteria for dividing myopathy, neuropathy, and normal were whether there are one of small amplitude-short duration, high amplitudes-long duration, reduced recruitment, early recruitment, and reduced interference pattern during minimal, moderately and maximally contraction. This study was approved by the Internal Review Board of Seoul National University Hospital (No. 2008-055-1147) and conducted according to the Declaration of Helsinki and its later amendments. Informed consent was not obtained because this study is retrospective analysis. EMG was performed with a monopolar needle electrode from muscles of subjects body (Viking Quest (Natus, USA)). The filter setting was set at 20 Hz (low-cut) and 10 kHz (high-cut). The results of the last 10 seconds of the EMG were recorded and used for analysis. Based on the elbow joint of the upper extremity and the knee joint of the lower extremity, the muscles close to this joint were classified as proximal muscles and distal muscles.

The results of the waveform data of patients stored numerically in the electromyography machine were extracted, and they were made into a waveform form through the MATLAB software (version R2020b) program and edited into a form suitable for analysis. The result of removing noise such as motion artifact that occurred while moving the needle electrode during the EMG test was used for analysis.

The raw EMG data, which was originally sampled at 48 kHz, was downsampled to 10 kHz for reducing computational complexity and sliced into multiple segments with a fixed length (0.4 seconds) which was decided after the experiment. After slicing, total segments were composed of 2700 segments from subjects with myopathies, 3664 segments of subjects with neuropathies, and 1706 segments of subjects without neither neuropathy nor myopathy.

**Building machine learning models**

One dimensional convolutional neural network was used to identifying EMG signal characteristics. nEMGNet

근전도 신호의 특징을 찾기위해 기존에 이미지의 분류에 효과를 입증받은 VGGNet과 ResNet에서 기반한 1차원 CNN을 사용했고 이를 nEMGNet으로 명명했습니다. nEMGNet의 구조는 3종류의 block으로 구성됐고 spatial reduction block-1은 spatial resolution을 반으로 줄이고 spatial reduction block-2는 spatial resolution을 4로 줄이고 residual block은 복잡한 특징을 찾아내기 위한 deep layer를 위한 안정적인 training을 가능하게 한다. Residual block의 개수를 달리해서 4가지의 nEMGNet을 구축했습니다. Convolutional layer이후의 fully connected layer에는 rectified linear unit (ReLU)를 적용했습니다. 분석에 사용한 EMG signal의 길이가 달라서 Divide and Vote (DiVote) pipeline을 적용하였습니다. DiVote는 각 EMG signal을 homogeneous shape의 segment로 나눴고 feature extractor를 통해 3개의 signal segment prediction score로 변환했습니다. Signal segment prediction score는 soft voting에 의해서 muscle signal prediction score로 aggregate해서 muscle별로 EMG 결과를 도출했고 muscle signal prediction score를 subject별로 aggregate해서 subject feature를 도출했습니다. Subject feature를 도출할 때 muscle을 proximal과 distal muscle로 구분한 추가정보를 넣고 분석한 것 (all)과 추가정보 없이 분석한 것 (proximal/distal) 2가지를 실험했습니다.

머신러닝은 convolutional neural network를 이용하여 근전도 파형을 분석하였음. 48Hz의 frequency로 분석하였고 0.2초 정도의 시간간격으로 데이터를 분할하여 학습시키고 validation및 적용을 하였음. 이후 환자의 최종임상 진단 중 myopathy, neuropathy, normal어디에 해당하는지의 결과와 머신러닝을 이용해 분석한 결과를 비교하여 정확도를 구했음 총 58명의 데이터로 상대적으로 수가 적어서 5-fold cross validation을 하여 final performance로

**Statistical analysis**

Statistical analyses were performed using R statistical software (version 4.1.0; R Foundation for Statistical Computing, Vienna, Austria). The *p*-value less than 0.05 was considered statistically significant.

**Results**

신경병은 radiculopathy, axonal neuropathy, motor neuron disease 의 환자를 대상으로 하였고 근육병은 muscular dystrophy, inflammatory myopathy 등의 환자를 대상으로 하였음. (Table 1)

Table 1. Demographic characteristics

Figure 1. Examples of electromyography waveform

Table 2. Accuracy of deep learning

Table 3. Confusion matrix

Figure 2. Architecture of deep learning algorithms

근전도 데이터를 머신러닝을 이용해서 분석한 결과 60%후반에서 80%초반의 정확도를 보였음. 정상과 근육병을 감별하는 결과는 ~%, 근육병과 신경병을 구분하는 결과는 ~%, 정상과 신경병을 구분하는 결과는 ~%의 결과를 보였음.

**Conclusions**

Recently, deep learning has been successfully applied to assisting diagnosis of medical diseases in so many ways.

We applied convolutional neural network to classification of volitional EMG waveforms via making numerical EMG data into waveform, editing and re-transforming into waveform data. Result of analysis showed that EMG waveform was well classified by deep learning algorithm. Our deep learning model might reduce error rate of EMG interpretation and physicians workload. This study suggest that the models built on deep learning-based EMG waveform interpretation might be complementary for physicians’ interpretation and promising.

Deep learning has shown good performance in many medical data including waveform and time series data such as electrocardiography and electroencephalography. In the analysis of waveforms of EMG, deep learning algorithm showed favorable performance compared with analyzed by physician and residents.

Until now, a few studies on analyzing EMG waveforms by deep learning have been documented.

In most cases, the accuracy and reliability of EMG interpretation by physician has been reported about 36-64% of the sensitivity, 54-58% of the specificity, 60-90% of inter-rater reliability. Interpreting the EMG might be difficult task for experienced physicians. From 6 different residents, the sensitivity was ~%, the specificity was ~%, and inter-rater concordance was ~%. With applying the deep learning algorithms, those were ~%, ~%, and ~%.

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