**Diagnostic usefulness of electromyography waveforms using deep learning: classification between neuropathy, myopathy and normal by convolutional neural network**

**Introduction**

Electromyography(EMG), which shows the electrical activity in muscle, has been used for distinguished between peripheral nervous system disorders and muscle disorders. Electrical signals from nerves and muscles help to identify electrophysiologic abnormalities. Electromyography is a test that inserts a needle into a muscle to check for abnormal spontaneous potential and displays it as a waveform which is transformed from motor unit action potential generated by contracting the muscle. The diagnostic usefulness of electromyography for identifying peripheral neuropathy and myopathy has been suggested in previous studies.

Recently, artificial intelligence (AI) has been used to analyzing big data in many field, and it is also applied to clinical data. Especially, deep learning techniques applied to clinical data include convolutional neural network, recurrent neural network. Convolutional neural network has applied in image and time series data. By using a convolutional neural network to analyze the waveforms of electrocardiography, electroencephalography.

The commonly known accuracy of EMG diagnotics is known as about 70% .(VASILIOS C CONSTANTINIDES, 2018) In order to increase the accuracy of elctrophysiological diagnosis through electromyography, we examined the effect of using deep learning. Implementing the deep learning techniques to analyzing the EMG complement the accuracy of electrophysiologic diagnosis in that EMG testing is repetitive testing in some muscles and interpreting the EMG result is subjective.

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.

근전도는 needle을 근육에 삽입하여 비정상적인 자발전위의 여부를 확인하고 근육을 수축시켜 motor unit action potential을 보고 이상을 확인하여 이를 통해 진단을 하는 검사임. 근육병, 신경병을 진단하는 데 있어 근전도의 유용성은 이전의 연구에서 밝혀진 바 있음. 근전도 검사의 정확도는 대략 ~%정도라고 알려져 있음. 따라서 임상에서 진단을 하는데 있어 추가적인 도움이나 도구가 있다면 정확한 진단을 하는데 있어 도움이 될 수 있을 것임.

근전도 검사와 유사한 전기신호의 파형을 이용한 검사로는 심전도, 뇌파 등이 있음. 이러한 심전도와 뇌파 검사를 machine learning을 이용해서 분석한 결과 정확도가 증가했다는 이전 연구결과가 있음. 그리고 기존에 근전도 검사를 분석하는 데 machine learning의 convolutional neural network를 이용하여 파형을 분석하였음.

이번 연구는 근전도 검사의 파형이 아닌 원래 데이터의 시간순서에 따른 intensity를 이용하여 분석했다는 점에서 기존의 연구와 차이점이 있다. 분석결과 기존 파형을 이용한 연구의 진단 정확도는 ~%였던 반면 이번 연구의 정확도는 ~%정도를 보여 임상적인 유용성이 있을 것으로 판단하여 보고를 하게 됐다.

**Methods and materials**

**Subjects and EMG recording**

The data analyzed in this article are from the Seoul National University Hospital database that includes electromyography data of 59 subjects, visited Seoul National University Hospital from Jun, 2015 to Jul, 2017, divided into 3 datasets which composed neuropathy, myopathy and normal. This study was approved by the Internal Review Board of Seoul National University Hospital and conducted according to the Declaration of Helsinki. Informed consent was not obtained because this study is retrospective analysis. EMG was performed with monopolar needle electrode from muscles of upper extremity or lower extremity (Viking Quest (Natus, USA). The filter setting was set at 20 Hz (low-cut) and 10 kHz (high-cut). During the test, 10 s of signals were averagely recorded. The following several motor unit action potentials were studies: [1] minimal contraction, [2] moderately contraction and [3] maximally contraction. The waveform diagnosis was made according to characteristics of respective waveforms which were neurogenic potentials or myopathic potentials or not. 2015.6~2020.7. Clinical demographic characteristics are summarized in table 1.

**Deep learning algorithm**

2018년?부터 2020년까지 서울대병원를 내원하여 근전도검사를 받은 환자를 대상으로 하였음. 정상, 근육병, 신경병 각각 20명의 대상자의 데이터를 이용함. 신경병은 radiculopathy, axonal neuropathy, motor neuron disease 의 환자를 대상으로 하였고 근육병은 muscular dystrophy, inflammatory myopathy 등의 환자를 대상으로 하였음. 근전도 데이터는 근육을 수축시켜서 motor unit action potential을 발생시킨 뒤 이를 기계에 저장한 데이터 중 10초 정도의 데이터를 가지고 분석하였음. 상지는 elbow joint를 기준으로 하지는 knee joint를 기준으로 이보다 가까운 쪽 근육은 proximal, 먼쪽 근육은 distal로 구분하여 분석을 진행함. 근육병, 신경병, 정상을 진단하는 기준은 임상적으로 근력이나 감각저하 등의 신경학적 검진과 근전도에서 recruitment 의 감소, interference pattern의 감소, motor unit action potential amplitude의 증가와 duration의 증가 를 신경병으로 early recruitment, motor unit action potential amplitude의 감소와 duration의 감소를 가지고 판단하였음.

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

Figure 1 depicted schematic of deep learning algorithm.

**Results**

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.

Table 2 shows the results of prediction by deep learning. Table 3 shows comparing the accuracy between this algorithm and others from previous other studies.

**Conclusions**

EMG, electrophysiologic examination which is used to differentiate between neurologic disorders or muscle disorders or normal, showed clinical usefulness in previous studies. However, the accuracy of EMG was limited because of interpretation by subjective characteristics and rapid passing of waveforms. Therefore, further study for more accurate interpretation of EMG is needed. In this study, we investigated the possibility of applying deep learning to analyzing EMG wave forms. With first model, the accuracy was 70% and increased to 80% by improving the algorithm and also showed better outcome with accurarcy of interpretation by physician (i.e. trainee such as residents in departments of neurology and rehabilitational medicine).

Recently, deep learning algorithm has been applied in a wide range of fields including clinical fields such as patient diagnosis and treatment.