**Studies on the usefulness of applying deep learning to classifying neuropathy, myopathy, or normal EMG waveforms**

**Introduction**

Electrophysiologic examination is used to identifying neuromuscular diseases, helping to estimate the location and extent of lesions. Electromyography (EMG), which is one of electrophysiological examination and records the electrical activity generated by the muscles, has been used for identifying whether there is any electrophysiologic abnormality of the nerve or muscle. To identify those disorders, we insert a needle into the muscle to see any abnormal waveforms shown with electromyography device made by any 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) For diagnosing neuropathy and myopathy, higher accuracy of electromyography is required, and objective interpretation is required by decreasing the discrepancy between raters.

Recently, deep learning has been used to analyzing big data in many field, and it is also applied to clinical data. 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.(15)

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**

**Data acquisition and preparation**

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

**Training and validation**

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

This study was reviewed and approved by the institutional review board of Seoul National University Hospital (IRB No.: 2008-055-1147, 과제명: 2020-3046, SOP버전: sop-04버전(2014.11.15)(2015.05.15)) and was conducted in accordance with the 1964 Helsinki declaration and its later amendments. Their medical history, clinical manifestations, and vascular risk factors were reviewed from medical record at the Seoul National University Hospital.

**Deep learning architecture**

**Statistical analysis**

**Results**

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**

EMG

1. Aminoff MJ, Goodin DS, Parry GJ, Barbaro NM, Weinstein PR, Rosenblum ML. Electrophysiologic evaluation of lumbosacral radiculopathies: electromyography, late responses, and somatosensory evoked potentials. Neurology. 1985;35(10):1514-8.

2. Bromberg MB. The motor unit and quantitative electromyography. Muscle Nerve. 2020;61(2):131-42.

3. Daube JR, Rubin DI. Needle electromyography. Muscle Nerve. 2009;39(2):244-70.

4. Leblhuber F, Reisecker F, Boehm-Jurkovic H, Witzmann A, Deisenhammer E. Diagnostic value of different electrophysiologic tests in cervical disk prolapse. Neurology. 1988;38(12):1879-.

5. Rubin DI. Needle electromyography: Basic concepts. Handb Clin Neurol. 2019;160:243-56.

6. Tonzola RF, Ackil AA, Shahani BT, Young RR. Usefulness of electrophysiological studies in the diagnosis of lumbosacral root disease. Ann Neurol. 1981;9(3):305-8.

7. Whittaker RG. The fundamentals of electromyography. Pract Neurol. 2012;12(3):187-94.

8. Haldeman S, Shouka M, Robboy S. Computed tomography, electrodiagnostic and clinical findings in chronic workers' compensation patients with back and leg pain. Spine (Phila Pa 1976). 1988;13(3):345-50.

9. Khatri BO, Baruah J, McQuillen MP. Correlation of electromyography with computed tomography in evaluation of lower back pain. Arch Neurol. 1984;41(6):594-7.

10. Kuruoglu R, Oh SJ, Thompson B. Clinical and electromyographic correlations of lumbosacral radiculopathy. Muscle Nerve. 1994;17(2):250-1.

11. Nardin RA, Patel MR, Gudas TF, Rutkove SB, Raynor EM. Electromyography and magnetic resonance imaging in the evaluation of radiculopathy. Muscle Nerve. 1999;22(2):151-5.

12. Haig AJ, Tong HC, Yamakawa KS, Quint DJ, Hoff JT, Chiodo A, et al. The sensitivity and specificity of electrodiagnostic testing for the clinical syndrome of lumbar spinal stenosis. Spine (Phila Pa 1976). 2005;30(23):2667-76.

13. Wu ZA, Tsai CP, Yang DA, Chu FL, Chang T. Electrophysiologic study and computerized tomography in diagnosis of lumbosacral radiculopathy. Zhonghua Yi Xue Za Zhi. 1987;39(2):119-25.

14. Kendall R, Werner RA. Interrater reliability of the needle examination in lumbosacral radiculopathy. Muscle Nerve. 2006;34(2):238-41.

15. Ribeiro AH, Ribeiro MH, Paixão GMM, Oliveira DM, Gomes PR, Canazart JA, et al. Automatic diagnosis of the 12-lead ECG using a deep neural network. Nat Commun. 2020;11(1):1760.