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

**Introduction**

Electromyography (EMG) is an electrophysiologic test that records electrical activity generated from nerves, muscles, and neuromuscular junctions at rest and during muscle contraction controlled by nervous system through needle inserted into the muscle. (1-6) 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. (1-6) Among signal shown on EMG, motor unit action potentials (MUAPs) is used to characterizing whether normal or neuropathy or myopathy. Typical neurogenic MUAPs, commonly observed in neurological diseases, are known to have large amplitudes, long durations, reduced recruitments, and reduced interference patterns, whereas myopathic MUAPs are known to have small amplitudes, short durations, and early recruitments and interference patterns. The diagnostic usefulness of electromyography for identifying peripheral neuropathy and myopathy has been suggested in previous studies. (1, 3, 4, 7-10)

Although electromyography plays an important role in diagnosing normal, neuropathy and myopathy, it has some limitations in that there are discrepancies among examiners, and the accuracy of EMG relies to a lot extent on proficiency of the examiner. Previous studies have reported that sensitivity of EMG in the diagnosis of neuropathy, myopathy, and normal is 47-83%, specificity is 73-81% and inter-rater reliability is 62-81%.(7, 9-18) Additionally, to recognize abnormalities of EMG waveform accurately, considerable time and efforts are needed. As the prevalence of neuropathy and myopathy continues to increase, the frequency of EMG for diagnosing it, the time it takes to interpret it, and the workload of the examiner are bound to increase. A new approach may be helpful in clinically diagnosing neuropathy or myopathy through EMG more efficiently and accurately in a shorter time.

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.(19) To our knowledge, previous studies on analyzing volitional EMG data have rarely been reported.

In order to overcome the shortcomings of electromyography and provide a more efficient test analysis method, deep learning was applied to the EMG waveform analysis, and to evaluate the accuracy of the machine learning-based EMG analysis, the interpreting results of physicians performing EMG were compared. For this study, 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 59 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 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.

**Training and validation**

상지는 elbow joint를 기준으로 하지는 knee joint를 기준으로 이보다 가까운 쪽 근육은 proximal, 먼쪽 근육은 distal로 구분하여 분석을 진행함. 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

**Deep learning architecture**

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이런식으로 그림 만들어서.

**Statistical analysis**

**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 ~%.

**References**

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

2. Mills KR. The basics of electromyography. Journal of Neurology, Neurosurgery & Psychiatry. 2005;76(suppl 2):ii32-ii5.

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

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

5. Kimura J. Electrodiagnosis in Diseases of Nerve and Muscle: Principles and Practice: Oxford University Press; 2013.

6. Oh SJ. Clinical Electromyography: Nerve Conduction Studies: Lippincott Williams & Wilkins; 2003.

7. 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.

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

9. 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-.

10. 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.

11. 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.

12. 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.

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

14. 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.

15. 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.

16. 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 (Taipei). 1987;39(2):119-25.

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

18. Nirkko AC, Rösler KM, Hess CW. Sensitivity and specificity of needle electromyography: a prospective study comparing automated interference pattern analysis with single motor unit potential analysis. Electroencephalogr Clin Neurophysiol. 1995;97(1):1-10.

19. 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. Nature Communications. 2020;11(1):1760.