Clinical Neurophysiology 130 (2019) 617–623

Contents lists available at ScienceDirect

Clinical Neurophysiology

journal homepage: www.elsevier.com/locate/clinph

Deep learning for waveform identification of resting needle electromyography signals

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ARTICLE INFO

Article history:
Accepted 28 January 2019
Available online 23 February 2019

Keywords:
Needle electromyography
Deep learning
Artificial neural network
Data augmentation
Resting discharge

HIGHLIGHTS

- Resting EMG discharges were classified by Mel-spectrogram conversion and deep-learning algorithms.
- Data augmentation and use of pre-trained weights (transfer learning) increased the accuracy.
- Waveform identification of clinical EMG testing might be possible by deep-learning algorithms.

ABSTRACT

Objective: Given the recent advent in machine learning and artificial intelligence on medical data analysis, we hypothesized that the deep learning algorithm can classify resting needle electromyography (n-EMG) discharges.
Methods: Six clinically observed resting n-EMG signals were used as a dataset. The data were converted to Mel-spectrogram. Data augmentation was then applied to the training data. Deep learning algorithms were applied to assess the accuracies of correct classification, with or without the use of pre-trained weights for deep-learning networks.
Results: While the original data yielded the accuracy up to 0.86 on the test dataset, data-augmentation up to 200,000 training images showed significant increase in the accuracy to 1.0. The use of pre-trained weights (fine tuning) showed greater accuracy than "training from scratch".
Conclusions: Resting n-EMG signals were successfully classified by deep-learning algorithm, especially with the use of data augmentation and transfer learning techniques.
Significance: Computer-aided signal identification of clinical n-EMG testing might be possible by deep-learning algorithms.

1. Introduction

Recent advent of artificial intelligence (AI) has been widespread in whole society. In health care, various applications using AI have emerged in a number of fields. Among many algorithms that are employed in AI or machine learning, the deep learning algorithm, one of the complex utilizations of neural network, is a recent technical breakthrough and enables complex identification of image and audio data (LeCun et al., 2015).

There is long history of quantification of waveforms in needle electromyography (n-EMG) to attempt automatic classification (Fuglsang-Frederiksen, 2006; Farkas et al., 2010). In addition to a long list of algorithms and features, experienced electromyographers have relied on audio information in identifying discharges. For example, some electromyographic discharges are nicknamed after similar audio events such as "sea shell" sound for endplate noise, and "dive bomber sound" for myotonic discharges (Daube and Rubin, 2009; Kimura, 2013). Therefore, we are interested in audio features of n-EMG discharges as a useful method for waveform identification. Among many techniques of audio analysis, conversion of audio signal to an image, such as a spectrogram, is

Abbreviations: AI, artificial intelligence; CNN, convolutional neural network; EMG, electromyography; GPU, graphic processing unit; MUAP, motor unit action potential; MUP, motor unit potential; n-EMG, needle electromyography; SGD, stochastic gradient descent.

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https://doi.org/10.1016/j.clinph.2019.01.024
1388-2457/

promising because it can be studied by modern imaging methodologies such as deep learning algorithm, as previously applied to detection of events in electroencephalography (Cecotti, 2017). Therefore, the aim of the present study was to study whether n-EMG discharges can be classified by the deep learning algorithm.

2. Methods

2.1. Subjects and n-EMG recording

This study was approved by the Internal Review Board of Tokushima University Hospital. Informed consent was obtained from the research subjects. In this prospective study, data were obtained from the patients who had n-EMG testing in the electromyography lab, Tokushima University Hospital between Jan, 2016 and Dec, 2017 for routine clinical indications. n-EMG was performed with concentric, 30-gauge needle electrodes from either biceps brachii, first dorsal interosseous, vastus medialis, or tibialis anterior muscles (Viking Quest (Natus, USA). The filter setting was set at 20 Hz (low-cut) and 10 kHz (high-cut). During the testing, up to 20 s of signals were recorded, when indicated. The following six resting potentials were studied: [1] complex repetitive discharges (CRDs); [2] endplate potentials (including both endplate noise and endplate spikes); [3] fasciculation potentials; [4] fibrillation potentials/positive sharp waves (PSW); [5] myotonic discharges; and [6] noise artifacts (including motion and 60-Hz artifacts). The waveform diagnosis was made according to definitions of respective waveforms (Kimura, 2013).

2.2. Retrieval of data and preparation of Mel-spectrogram

The recorded data were reviewed by a certified electromyographer (HN) who selected appropriately recorded video files. Only the audio component from the video was extracted thereafter. Note that the "audio" signal is identical to the original recording, thus no conversion was performed in this process. The audio root-mean-square volumes of the recorded files (single channel, frequency = 44,100 Hz) were normalized to −26 dB (by the 'ffmpeg-normalize' program, https://github.com/slhck/ffmpeg-normalize). The obtained data were divided into 2-s segments [Adobe Audition 2017CC (Adobe Systems Inc, USA)], that yielded up to four files from a single file. The segmented data were then reviewed by another certified electromyographer (YO) who was not aware of the clinical information.

Spectrogram is commonly used for visualization of signals, which is a Fourier Transform of raw audio signals and shows frequency content as a function of time. In comparison with simply visualizing raw audio signal, several techniques achieve greater accuracy in similar problems such as speech recognition, detection of emotion, and music genre recognition. Mel-spectrogram (or Mel-powered power spectrogram) has been recognized as one of the most useful methods because Mel scale adequately reflects human perception of audio signals (Chen et al., 2017). Mel-spectrogram was created from each 2-s audio data by librosa package, version 0.5.1 (McFee et al., 2015) with the following parameter settings (x_axis = time, y_axis = mel, fmax = 8000, normalization = True, colormap = viridis). The mel-spectrograms were then divided into training (80%) and validation data (20%).

In addition to original audio data, data augmentation was performed to increase the volume of training data (Bloice, 2018). The original Mel-spectrograms were processed by the following techniques, that created a total of either (1) 2000, (2) 20,000, or (3) 200,000 training images: (a) skew (probability = 0.5) (b) random distortion (probability = 0.25, grid-width = 16, grid-height = 16, magnitude = 8), and (c) random distortion (probability = 0.25, grid-width = 24, grid-height = 24, magnitude = 16) (Supplementary Figs. 1 and 2).

2.3. Deep learning algorithm

Computation was performed by an Ubuntu18.04-based personal computer that was equipped with two graphic processing units (GPUs) (NVIDIA GeForce GTX 1080Ti). Deep learning was performed by using Python 3.5.6 and MXNet 1.2.0 (Doi, 2018). The following popular network architectures were used with different depths of layers: VGG net (layer depths of 11 or 19), and ResNet (layer depths of 50, or 152), and Inception-v3. For each architecture, training and validation processes were performed as follows: (1) the use of random initial weights of networks ("from scratch") by training the original data alone or augmented data, and (2) training with publically available pre-trained models ("fine-tuning") with training one additional layer, training either by the original data or the augmented data. The following common hyperparameters were used: the initial learning rate at 0.001 gradually decreasing by 0.1 on every 10 epochs, the optimizer = stochastic gradient descent (SGD). For evaluating metrics of the validation dataset, accuracy, precision, recall, and F1-score were calculated along with a confusion matrix [definitions (True Positive = TP, False Positive = FP, False Negative = FN, True Negative = TN): (1) precision = TP/(TP + FP); (2) recall = TP/(TP + FN); (3) F1-score = (2 * precision * recall)/(precision + recall)]. The overall flow of analyses is summarized in Fig. 1.

3. Results

3.1. Clinical characteristics

A total of 330 n-EMG files were obtained from 83 patients. The patients had the following clinical diagnoses: (1) CRDs (62 files from 16 subjects): amyotrophic lateral sclerosis, radiculopathy; (2) endplate potentials (26 files from 12 subjects): myalgia of undetermined significance, radiculopathy, central weakness, cubi-

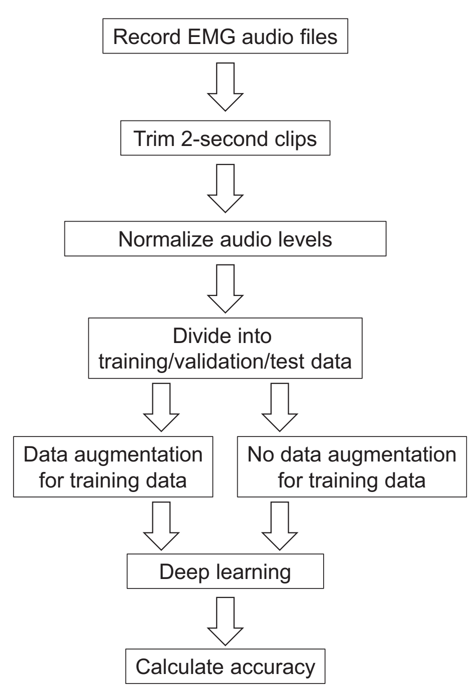

Fig. 1. Overall flow of data analysis including data collection, image transformation, and deep learning.

tal tunnel syndrome carpal tunnel syndrome; (3) fasciculation potentials (61 files from 25 subjects): multifocal motor neuropathy, amyotrophic lateral sclerosis, benign fasciculation syndrome, Kennedy disease; (4) fibrillation potentials/PSW (75 files from 28 subjects): polymyositis, amyotrophic lateral sclerosis, muscular dystrophy, peripheral nerve injury, radiculopathy; (5) myotonic discharges (55 files from 17 subjects): myotonic dystrophy type 1, radiculopathy; (6) Noise artifact (51 files from 31 subjects) including 60 Hz- and motion-artifacts: carpal tunnel syndrome, radiculopathy, peripheral nerve injury polymyositis.

3.2. Deep learning of n-EMG signals

3.2.1. Preparation of input Mel-spectrogram

A total of 330 Mel-spectrograms of resting discharges were available for analysis, that were randomly divided into training (N = 271) and validation (N = 59), by maintaining the frequencies of the classes. Fig. 2 shows representative Mel-spectrogram images that show distinctive image features of respective resting discharges. Essentially, Mel-spectrogram represents an acoustic time-frequency relationship of a sound (Supplementary Fig. 3).

3.2.2 Deep-learning

By using the Mel-spectrograms as visual inputs, the following three deep-learning analyses were performed. The first protocol used random initial weights ("training from scratch") trained by either (1) original data or (2) augmented data (N = 20,000) (Table 1, Supplementary Figs. 1, 2 & 4). The deep-learning networks were trained by the respective training data. Then separate validation data were applied to assess the generalizing ability of classifiers. The original data yielded validation accuracies ranging 0.52–0.86 depending on the deep-learning networks. In comparison with the original data, the accuracies significantly increased by data augmentation in four of the five deep-learning networks by 0.14–0.40. Thus, data augmentation was considered to be useful in achieving high accuracy.

In order to further elucidate the effect of data augmentation, the size of data-augmentation was changed (Table 2, Fig. 3). By increasing the size of the augmented training data from 2000 to 200,000, the validation accuracies increased by 0.01–0.05 in four of the five deep-learning networks. Even significantly increasing the training epochs (from 50 to 2000), the use of original data yielded lower accuracies than those with the augmented data, again implying the advantage of data augmentation. Intriguingly, more complex deep-learning networks did not yield higher validation accuracies (e.g., VGG16 vs. VGG19; ResNet50 vs. ResNet152: the greater number implies greater numbers of layers and more complex structures), possibly because of overfitting in complex networks with relatively small datasets. Overfitting refers to a model where the training data are reflected too well (like memorizing the answers of a small textbook), such that the model cannot generalize, or yields poor classifying results on new data. Table 3 shows the confusion matrices by the different sizes of data augmentation and the use of pre-trained weight. In the confusion matrices, the diagonal sequence (from upper left to lower right) suggests correct classification (predicted class = labelled class), outside of which indicates misclassification. These matrices indicate greater accuracies with the use of pre-trained weights ("fine tuning") and greater number of data augmentation.

Besides validation accuracy, other evaluation metrics were compared in Table 4. Similar to the validation accuracy, three metrics (precision, recall, and F1-score) were higher by data augmentation and the use of pre-trained weights.

Table 1
The highest validation accuracies by models with random initial weights ("training from scratch") (the number of epochs = 500). The results imply advantages of data augmentation in most of the deep-learning algorithms.

Deep-learning networks	Original training data (N = 271)	Data-augmented (N = 20,000)
VGG16	0.86	0.86
VGG19	0.80	0.94
ResNet50	0.70	0.94
ResNet152	0.52	0.92
Inception-v3	0.77	0.94

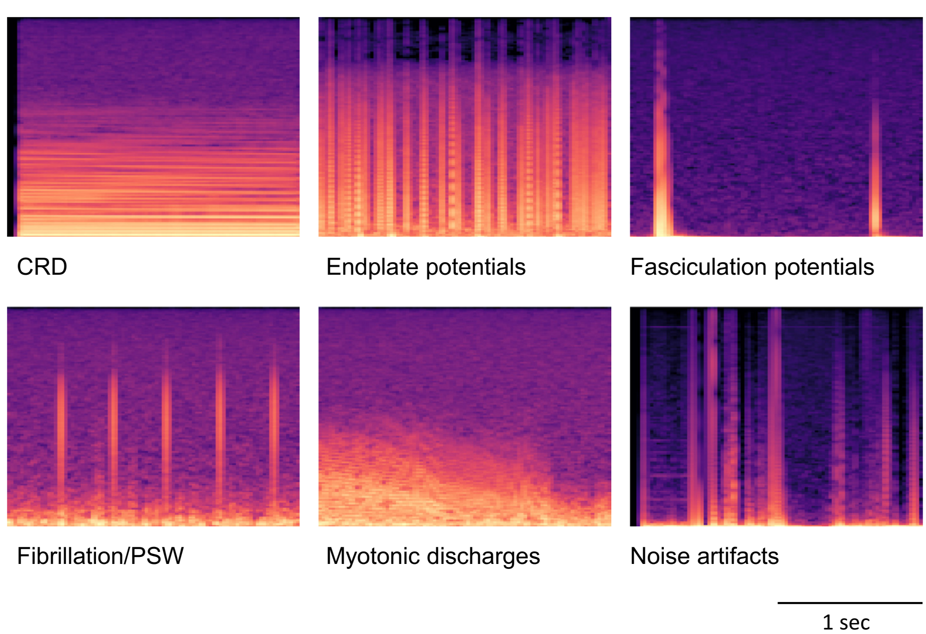

Fig. 2. Representative Mel-spectrogram of six resting n-EMG discharges. Mel-spectrogram is an acoustic time-frequency representation. The scale magnitude is demonstrated by the following color order: yellow > orange > purple. CRD = complex repetitive discharges; PSW = positive sharp waves.

Table 2
The best validation accuracies with publically-available pre-trained models were used, on top of which one additional layer was added (fine-tuning). After finishing the mentioned epochs of training cycles, the best weight was saved according to the validation accuracies of each epoch. (A) In comparison with the data in Table 1, fine-tuning showed greater accuracies than "training from scratch" with the original, non-augmented training data. (B) The validation accuracies were further greater with data augmentation. The number of epochs: (1) 50 and 2,000 (using the original training data) and (2) 50 (using the augmented training data number = 2000, 20,000, and 200,000).

Deep-learning networks	Original training data (N = 271) *50/2000 epochs	Data augmented (N = 2000) *50 epochs	Data augmented (N = 20,000) *50 epochs	Data augmented (N = 200,000) *50 epochs
VGG16	0.97/0.97	0.97	0.97	0.98
VGG19	0.94/0.94	0.97	0.97	0.97
ResNet50	0.89/0.95	0.95	0.98	1.0
ResNet152	0.94/0.97	0.97	0.97	0.98
Inception-v3	0.83/0.95	0.92	0.97	0.97

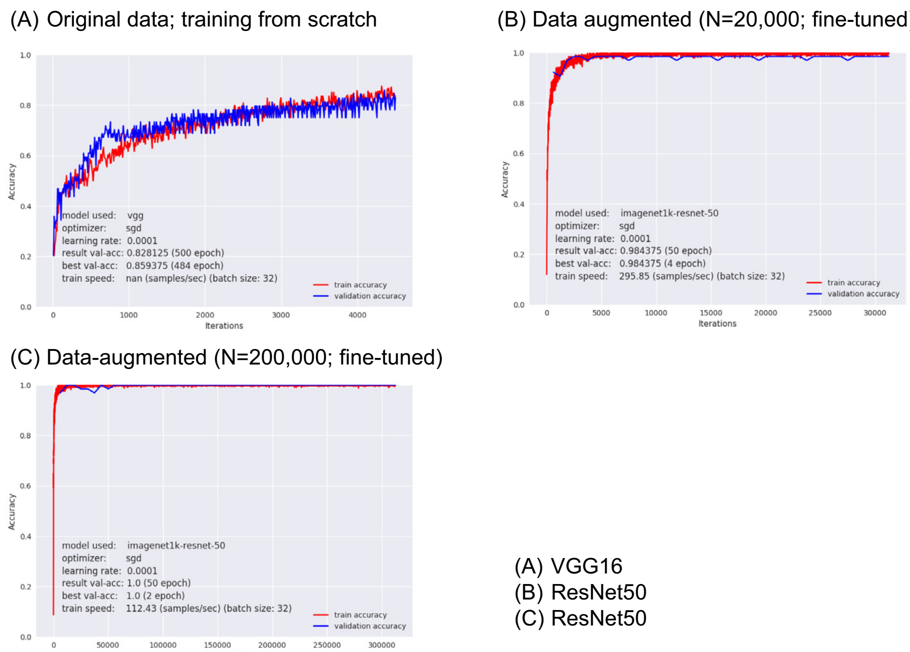

Fig. 3. Learning and validation curves by different training settings. with or without data augmentation and pre-trained weights, using both showed greater training and validation accuracies. Use of the original data alone (without data augmentation) and no use of pre-trained weights (panel A) yielded much lower accuracies than using the augmented training data (panels B and C), even by increasing the number of epochs from 50 to 500 (panel A). The data suggest advantage of data augmentation and use of pre-trained weights (fine-tuning). See details in Tables 1 and 2.

4. Discussion

In this study, we applied one of the most promising algorithms in machine-learning, deep-learning, to classification of six forms of resting n-EMG discharges via transformation of 2-s audio files into Mel-spectrogram. Our data showed that the discharges were successfully classified, especially by data augmentation and pre-trained neural networks. The results of the present study could lead to an AI-based n-EMG discharge classification system.

4.1. Application of deep learning to n-EMG

Signal identification is a complex task. As many clinical electromyographers consciously or unconsciously practice, they could analyze many factors from resting n-EMG discharges, such as waveforms of a single discharge, intervals and stability of discharges, onset-offset patterns, and characteristic audio signals. In order to quantitatively analyze various patterns of resting n-EMG discharges, assessment of these many factors could provoke a challenging task and often require forms of automatic analyzing system, such as machine learning, a subfield of computer science. The ultimate goal of machine learning is to explore the study and construction of algorithms that can learn from and make prediction on data (Brattain et al., 2018; Thrall et al., 2018). Among the many algorithms in machine learning, deep learning is a complex form of neural network, that has quickly evolved over the past decade and shown to surpass human eyes for object identification and other tasks (Voulodimos et al., 2018). The following groups have applied the deep learning algorithms to needle or surface electromyography, mostly on motor unit identification.

Sengur and colleagues recently compared patients with amyotrophic lateral sclerosis and healthy individuals (Sengur et al., 2017). Publically available data of n-EMG were collected and time–frequency representation of signals were employed by serial data conversion into spectrogram, continuous wavelet transform, and smoothed pseudo Wigner–Ville distribution. The data were then trained by a simple structure of convolutional neural network (CNN) and showed 96.69% accuracy to classify between the two classes by using spectrogram. Zhai and colleagues applied surface electromyography data of hand movements into the CNN algorithm (Zhai et al., 2017). They used short latency dimension-reduced surface EMG spectrograms as inputs, and claimed to have higher classification accuracy than traditional classifiers such as support-vector machine. Two other teams also reported the use

Table 3
Confusion matrices of the validation dataset with different training settings, using the parameters and deep-learning networks yielding the highest validation accuracy. The diagonal elements (in circles) represent the numbers of data where the predicted labels are identical to the true label, on the other hand off-diagonal elements are those that are mislabeled by the classifier. As shown in Tables 1 and 2, fine tuning and data augmentation resulted in greater classifying accuracies than the original data and "training from scratch". CRD = complex repetitive discharges; fasc = fasciculation potentials; fib = fibrillations/positive sharp waves; myotonia = myotonic discharges.

CRD (actual)	11	0	0	0	0	0
Endplate (actual)	0	4	0	1	0	0
Fasciculation (actual)	0	0	9	0	0	2
Fibrillation (actual)	0	0	0	12	0	1
Myotonia (actual)	1	1	0	1	7	0
Noise (actual)	0	0	1	1	0	7
	CRD (predicted)	Endplate (predicted)	Fasciculation (predicted)	Fibrillation (predicted)	Myotonia (predicted)	Noise (predicted)

(A) Original data; training from scratch (VGG16)

CRD (actual)	11	0	0	0	0	0
Endplate (actual)	0	5	0	1	0	0
Fasciculation (actual)	0	0	10	0	0	1
Fibrillation (actual)	0	0	0	13	0	1
Myotonia (actual)	0	0	0	0	10	0
Noise (actual)	0	0	0	0	0	9
	CRD (predicted)	Endplate (predicted)	Fasciculation (predicted)	Fibrillation (predicted)	Myotonia (predicted)	Noise (predicted)

(B) Data augmented (N=20,000; fine-tuned) (ResNet50)

CRD (actual)	11	0	0	0	0	0
Endplate (actual)	0	5	0	0	0	0
Fasciculation (actual)	0	0	11	0	0	0
Fibrillation (actual)	0	0	0	13	0	0
Myotonia (actual)	0	0	0	0	10	0
Noise (actual)	0	0	0	0	0	9
	CRD (predicted)	Endplate (predicted)	Fasciculation (predicted)	Fibrillation (predicted)	Myotonia (predicted)	Noise (predicted)

(C) Data-augmented (N=200,000; fine-tuned) (ResNet50)

of artificial neural network to be used as an electromyography classifier for prediction of hand grasp movements (Atzori et al., 2016; Gandolla et al., 2017).

Machine learning, or deep learning, can accept different forms of n-EMG data as input. Besides converting the n-EMG signals to a Mel-spectrogram as used in the present study, other methods have been used, even using raw signals. Furthermore, preprocessing data conversion have been proposed, such as Fourier transform, discrete Fourier transform, time-frequency analysis (e.g., short time Fourier transform, Wigner distribution), and cepstrum analysis (Raez et al., 2006). It would be intriguing how different data preparation affects accuracy.

4.2. Effects of data augmentation and fine tuning

Despite potentially high diagnostic accuracies in image classification tasks, the classifying and identifying power of deep learning is heavily dependent on a number of training data. For general image recognition tasks, the number of training image data is few thousands, at least, or even tens or hundreds of thousands in

Table 4
Evaluation metrics with different data setups and deep-learning networks. (1) precision = TP/(TP + FP); (2) recall = TP/(TP + FN); (3) F1-score = (2 * precision * recall)/(precision + recall) [TP = true positive, FP = false positive, FN = false negative].

	VGG16			ResNet50		
	Precision	Recall	F1-score	Precision	Recall	F1-score
Original data	0.95	0.95	0.95	0.90	0.90	0.90
Data augmented (N = 2000)	0.97	0.97	0.97	0.96	0.95	0.95
Data augmented (N = 20,000)	0.97	0.97	0.97	0.99	0.98	0.98
Data augmented (N = 200,000)	0.97	0.97	0.97	1.0	1.0	1.0
Data augmented: N = 20,000 (training from scratch)	0.94	0.93	0.93	0.93	0.92	0.92

challenging tasks. In healthcare-related researches, preparation of such a large number of training data is significantly difficult. To overcome such obstacles, two methods have been utilized, namely data augmentation and fine-tuning/transfer learning (Tajbakhsh et al., 2016; Hussain et al., 2017).

If a number of training data is small, overfitting tends to occur by learning from respective small samples too heavily. Because overfitted model lacks ability to classify samples other than the provided training data, it causes significantly poor classification in the test data, or data that are not previously trained. To avoid such overfitting and to increase generalized ability for classification, data augmentation is a popular technique for increasing the size of training dataset by applying class-preserving transformations, such as flipping, adding noises, size changes, cropping, among others (Hussain et al., 2017). Our data showed that data augmentation was effective to achieve greater validation accuracies in most of the deep-learning architectures, either with or without the use of pre-trained models.

Another technique to achieve high accuracy in image identification tasks is fine tuning that uses pre-trained deep learning models in non-medical general image datasets (Tajbakhsh et al., 2016). Since these models are trained by a large number of general images, they tend to learn very discriminative, and often generalized, features. Although pre-existing neural networks and their weights were based on image classification tasks of non-medical images, application of such pre-trained networks to medical images have been successful by many modalities such as ultrasound (Banzato et al., 2018), optical coherence tomography (Kermany et al., 2018), and plain radiograph (Kim and MacKinnon, 2018). Our data were in consistent with previous studies that transfer learning using pre-trained models increased the classification accuracy considerably (Table 3).

4.3. Limitations

This study has limitations. First, the number of files was small. Although this weakness appeared to be partially covered by data augmentation, a larger dataset would yield further improvement in accuracy. Additionally, fine tuning of hyperparameters on deep learning architectures could have further improve the accuracy. Second, it is unknown whether the deep learning algorithm can be directly applied to waveform identification in clinical practice. This study only covers 6 resting n-EMG discharges, that could be further increased, even including motor unit potentials. Collecting and other n-EMG patterns should be necessary for clinically usable systems. Another limitation could be different machine setting in each EMG laboratories, such as filters and needle properties. Even though audio signals are similar to human ears, the representations by different EMG machines could be significantly different. Comparison of different recording setting should be conducted in future. Third, we have not determined the adequate length of audio files. We arbitrarily decided a 2-s recording for two reasons: (1) too short recording might not detect rhythmicity of discharges as being present in fibrillation potentials and complex repetitive discharges, and (2) too long recording might be unstable and contaminated by external noise. Different durations should be studied to analyze the best accuracy. Fourth, we have not compared among visualization methods, such as Mel-spectrogram, plain spectrogram, chroma features, among others.

In summary, deep learning is a promising algorithm to correctly classify resting EMG potentials. Collection of larger number of data and refinement of analysis could further improve detection accuracy and enable its application to clinical practice.

Conflict of interest statement

None of the authors has conflict of interest to disclose.

Funding

This work was supported by JSPS KAKENHI Grant Number 17K09800.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.clinph.2019.01.024.

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