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Classification of amyotrophic lateral sclerosis disease based on convolutional neural network and reinforcement sample learning algorithm

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Abstract

Electromyogram (EMG) signals contain useful information of the neuromuscular diseases like amyotrophic lateral sclerosis (ALS). ALS is a well-known brain disease, which can progressively degenerate the motor neurons. In this paper, we propose a deep learning based method for efficient classification of ALS and normal EMG signals. Spectrogram, continuous wavelet transform (CWT), and smoothed pseudo Wigner–Ville distribution (SPWVD) have been employed for time–frequency (T–F) representation of EMG signals. A convolutional neural network is employed to classify these features. In it, Two convolution layers, two pooling layer, a fully connected layer and a lost function layer is considered in CNN architecture. The CNN architecture is trained with the reinforcement sample learning strategy. The efficiency of the proposed implementation is tested on publicly available EMG dataset. The dataset contains 89 ALS and 133 normal EMG signals with 24 kHz sampling frequency. Experimental results show 96.80% accuracy. The obtained results are also compared with other methods, which show the superiority of the proposed method.

Keywords: Electromyogram (EMG) signals, Time–frequency representation, Convolutional neural networks, Reinforcement sample learning and amyotrophic lateral sclerosis (ALS)

Introduction

Electromyography (EMG) signal measures electrical events of muscles, which provide more inside information for identification of neuromuscular disorders such as amyotrophic lateral sclerosis (ALS) [1]. ALS is a progressive neuromuscular disorder, which affects motor neurons by gradual degeneration and damage of neurons [2]. EMG signal is important tool for diagnosis of ALS disorder. Visual identification of EMG signals are challenging task, time consuming, which motivate to develop automatic identification method analysis and classification of ALS EMG signals.

Numerous methods have been developed for classification of ALS and normal EMG signals. Discrete wavelet

transforms based features used for identification of ALS EMG signals [3]. DWT with different classifiers have been used for multiclass classification of EMG signal [4, 5]. Cepstral coefficient employed for classification ALS and normal EMG signals [6]. Various features with linear discriminant analysis (LNA) classifier used for discriminate between ALS and normal EMG signals [7]. Bootstrap resampling method applied for identification of ALS EMG signals [8]. Short time Fourier transform based feature to diagnosis of ALS EMG signals [9]. DWT based features with K-nearest neighborhood (KNN) classifier have been employed for diagnosis ALS disorder [10]. Bispectrum based features have been used as features to ELM classifier for classification of EMG signals [11]. Time domain and wavelet decomposition based method explored for discrimination of EMG signals [12]. Numerous classifiers applied for diagnosis of muscular disorders [13, 14]. Time and frequency based features with support vector machine used for classification of EMG signals

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[15]. Dimension reduction methods have compared for classification of EMG signals [16].

In this paper, time–frequency (T–F) representation of EMG signals and convolutional neural networks (CNN) are used for classification of ALS and normal EMG signals. Spectrogram, CWT and SPWVD methods are considered for T–F representation. Two convolution layers, two pooling layer, a fully connected layer and a lost function layer is considered in CNN architecture. The training of the CNN was done with reinforcement sample learning strategy. The efficiency of the proposed implementation is tested on publicly available EMG dataset. The dataset contains 89 ALS and 133 normal EMG signals with 24 kHz sampling frequency. Experimental results show 96.80% accuracy.

The paper is structured as follows. Section 2 briefly describes the proposed method and the related theories such as spectrogram, CWT, SPWVD, CNN and reinforcement learning strategy. A graphical illustration of the proposed method can also be seen in this section. In Sect. 3, the experimental results are given. The paper is concluded in Sect. 4.

Proposed method

An illustrative representation of the proposed method is shown in Fig. 1. As seen in the Fig. 1, the input EMG signals were firstly filtered and normalized by hamming filtering and min–max normalization for sake of convenience for further steps of the proposed method [17, 18]. Filtered and normalized EMG signals were then fed into the time–frequency (T–F) representation. T–F representation enables to represent 1-D signals with 2-D images. To this end, three different T–F representation methods were used namely, Spectrogram, continuous wavelet

transform (CWT) and smoothed pseudo Wigner–Ville distribution (SPWVD). These T–F representations are formulated in Eqs. 1, 2 and 3, respectively. After T–F transformation, input EMG signals were represented by 2-D T–F coefficients. These coefficients were coded with unsigned integer values for representing them as images and resized. Feature extraction and classification stages are handled by using CNN. The adopted CNN architecture contains two convolution layers and two pooling layers. A fully connected layers and a lost function layer is next to the previous layers. The training of the CNN was done with reinforcement sample learning strategy.

Time frequency images

The Spectrogram, continuous wavelet transform (CWT) and smoothed pseudo Wigner–Ville distribution (SPWVD) time frequency representation are follows:

Spectrogram

In this subsection the theory of the spectrogram is briefly reviewed. The spectrogram of a given signal x is calculated as following;

$$X(\tau, \omega) = \int x(t)w(t - \tau)e^{-j\omega t} dt \quad (1)$$

where $w(t)$ is the window function. The magnitude squared of the STFT yields the spectrogram of the function: Spectrogram = $|X(\tau, \omega)|^2$.

Continuous wavelet transform (CWT)

The continuous wavelet transform (CWT), with respect to the wavelet ψ is a function of two variables $X(\tau, s)$ can be expressed as:

$$X(\tau, s) = \int x(t) \frac{1}{\sqrt{|s|}} \psi^* \left(\frac{t - \tau}{s} \right) dt \quad (2)$$

The position of wavelet in time and frequency domain is τ and s respectively.

Smoothed pseudo Wigner–Ville distribution (SPWVD)

The smoothed pseudo Wigner–Ville distribution (SPWVD) can be expressed as:

$$X(t, f) = \int h(\tau) \left\{ \int g(u - t) x \left(u + \frac{\tau}{2} \right) x^* \left(u - \frac{\tau}{2} \right) du \right\} \times \exp(-j\omega\tau) d\tau \quad (3)$$

where $x(\cdot)$ is the signal, t is the time, ω is the frequency, $g(\cdot)$ and $h(\cdot)$ are time and frequency smoothing Hamming window functions, respectively.

Let $X[p, q]$ represents the time frequency representation of the discrete time of the EMG signal $x[n]$ spanning over the samples $(1, N)$, where p and q represent indices corresponding to discrete-time and frequency respectively. The relation between p, q, t , and f is given by $p = tfs$, $q = 2fM/fs$. The index q takes integer values from 1 to M , where M denotes the index limit corresponding to half of the sampling frequency (fs).

Convolutional neural networks (CNN)

CNN is an important method for object detection [19]. For a given input image, CNN incorporates spatial information between pixels into the nodes of network. Generally, CNN architecture contains three basic layers: convolution, pooling, and fully connected layers. Convolution and pooling layers are embedded sequentially. Convolution and pooling operations construct the features. The classification is performed based on these features with the fully connected layer. In CNN architecture, there is a huge number of parameter that needs to be tuned during CNN training stage. The training of CNN is handled with the conventional back propagation algorithm.

The CNN architecture contains the following layers as:

- *Convolution layer* This layer contains a sequence of filters, whose coefficients are adjusted during the training process. In the training procedure of the CNN, each filter is convolved across the width and height of the input volume in the forward pass.
- *Pooling layer* Pooling layer aims to create a non-linear down-sampling. In other words, pooling partitions the input volume into a set of non-overlapping rectangle sub-regions and for each sub-region, the considered operation is applied for obtaining the out-

put. The pooling operation reduces the spatial size of input which also reduces the amount of parameters and computation in the network.

- *Fully connected layer* The classification process is carried out in fully connected layer. Neurons in this layer have full connections to all activations in the previous layer.

Reinforcement sample learning strategy

To speed up the training speed and efficiency, a new learning strategy, reinforcement sample learning strategy is employed here. The idea of reinforcement sample learning is to reinforce training the network on these samples with poor performance in the training procedure [20]. The detailed steps are described as follows:

1. Divide the samples into several batches randomly;
2. Train the model using all batches of samples in one epoch;
3. Identify the batches whose performance is lower than the criteria for the current epoch;
4. Tune the network only using these batches with more epochs;
5. Go to step 2 to train the model until the termination criterion are satisfied.

The criterion to identify the samples with poor performance is as follows:

$$C = \frac{1}{N} \sum_{j=1}^N Er^{(t)}(B_i) \quad (4)$$

where B_i is the batch of samples at t epoch and $Er^{(t)}(B_i)$ is the classification error rate of batch B_i at t epoch. N is the total number of batches. If the batch's error rate is greater than the C , it will be trained using more epochs.

In step 4, the network is tuned only on these batches with poor accuracy. The iteration epochs to tune are determined by a strategy based on their previous error rate. The idea is that the poorer performance, the more epochs will be employed to retrain the batch of samples. The repeated epoch number is determined by:

$$ReEp(B_i^{(t)}) = f(\Delta Er(i)) \quad (5)$$

$$\Delta Er(i) = |Er^{(t)}(B_i) - C| \quad (6)$$

where $f(\cdot)$ is a function to map the absolute difference value of Er and C to epoch number. In our experiment, we use a piecewise function to implement it.

Experimental results

The EMG dataset, which contains the ALS and normal EMG signals, was collected by the University of Copenhagen in 2001 [21]. While normal EMG signals were recorded on six males and four females, ALS EMG signals were acquired from four males and four females, respectively. The healthy group has an age interval from 21 to 37 years old and ALS group covers the age interval from 35 to 67 years old. A standard needle electrode was used for the signal acquisition. Sampling rate of EMG signals was almost 24 kHz and digitized by A/D convertor of 16-bit resolution. Recorded signals were filtered at 2 Hz and 10 kHz by high- and low-pass filters, respectively.

The dataset contains totally 202 EMG signals of which 89 of them were collected from ALS patients and 133 of

them were collected from healthy persons. Data augmentation was carried out by acquiring random samples from each EMG signals. 150 new EMG sequences with 10,000 samples were constructed from each EMG signal, which yielded totally 30,300 EMG sequences.

The obtained new EMG sequences were then transferred into T–F domain by applying T–F transformations such as spectrogram, CWT and SPWVD. In other words, 1D EMG signals were represented by 2D T–F images. In Figs. 2a and 3a, a time domain ALS and a normal EMG signals were presented. The x-axis of these figures shows the number of samples and the y-axis of these figures shows the related amplitude values. Similarly, Figs. 2b and 3b show the spectrogram representation of the time domain signals that are given in Figs. 2a and 3a,

Fig. 2 a ALS EMG signal, b Spectrogram representation of ALS EMG signal, c CWT representation of ALS EMG signal, d SPWVD representation of ALS EMG signal

respectively. While the x-axis of Figs. 2b and 3b shows the time (samples), the y-axis of these figures shows the frequency. Figs. 2c and 3c also show the CWT representation of the time domain signals, respectively. For these figures, the x-axis shows the time(samples) and the y-axis shows the scale. Finally, Figs. 2d and 3d show the SPWVD representation of the time domain signals that are given in Figs. 2a and 3a, respectively. The x-axis shows the time(samples) and the y-axis shows the frequency.

For spectrogram representation, the windowing operation was performed with Hamming window with length of 100. The number of overlap between adjoining segments was chosen as 80 and the number of sampling for discrete Fourier transform was selected as 100. For CWT, the analytic Morse wavelet with a symmetry parameter of

3 was used and a time-bandwidth product of chosen as 60. In addition the SPWVD was computed using for the sizes of the frequency and the time smoothing Hamming windows of 256 samples. The sizes of the time and frequency smoothing windows were not affected the classification accuracy, for lower window size computational complexity was more.

In deep learning section of the proposed method, a 6 layered CNN architecture was adopted with the following configuration: two convolutional layers, two pooling layers, one fully connected layer and one lost function layer. In the first and second convolutional layers, there are 64 and 32 filters of size 3×3 , respectively. The pooling layers have the same structure. 2×2 max pooling was considered in pooling layers. The fully connected

layer has the $64 \times 64 \times 2$ configuration. In the lost function layer, we use the soft-max function.

For training of the CNN model, randomly selected of 13,000 ALS and 16,000 normal EMG sequences were used and the rest 350 ALS and 950 normal EMG sequences were used for testing of the CNN model. As it was mentioned earlier, three T–F representation methods were considered for constructing the 2D T–F images. The obtained results are tabulated in Table 1. The obtained results were evaluated based on sensitivity, specificity and accuracy criterions, respectively.

As seen in Table 1, CWT yielded the highest accuracy and specificity values among the all investigated T–F methods. 98.80% specificity and 96.80% accuracy values were tabulated in the last row of Table 1. Moreover, CWT achieved the second highest sensitivity value (94.80%). In addition, the spectrogram representation based method obtained the second highest accuracy (96.69%) and specificity (97.59) values. It is worth to mentioning that the spectrogram based methods accuracy value was quite close to the CWT based method's accuracy value. Spectrogram method's accuracy was only 0.11% worse than the CWT method's accuracy. Spectrogram method's sensitivity and specificity values were also worse than the CWT method's sensitivity and specificity values. Unfortunately, the lowest evaluation results were recorded for SPWVD T–F representation method. SPWVD method's achievement on accuracy was almost 15% worse than the CWT method's achievements. In addition, the SPWVD was the most successful method in detection of ALS disease where 99.71% sensitivity value was obtained and spectrogram and CWT yielded similar ALS detection rate where the sensitivity values were 94.24 and 94.80%, respectively.

We also compared the proposed method with the methodology in [18] on ALS classification task. In [18], the authors proposed a texture based scheme for EEG classification. More specifically, in the methodology, the input EEG signals were firstly converted to T–F domain by spectrogram method and then the gray level co-occurrence features were extracted from each T–F images. Finally, a support vector machines classifier was used for classification of EEG signals into seizure or healthy. In Table 2, the obtained results on ALS classification were

Table 2 Performance comparison with Ref. [18]

Method	Sensitivity (%)	Specificity (%)	Accuracy (%)
Ref. [18]	89.66	78.96	85.44

Table 3 Performance comparison with other methods

Method	Sensitivity (%)	Specificity (%)	Accuracy (%)
Doulah et al. [6]	76	98	92.5
Misra et al. [22]	93	92.5	95
Proposed method (CWT)	94.8	98.8	96.8

given. When the results in Table 1 compared with the results in Table 2, it is obvious that CNN classification highly improved the evaluation values. The highest accuracy in Table 1 was almost 11% better than the accuracy in Table 1.

Another performance comparison of the proposed method with some other methods from literature was given in Table 3. As seen in Table 3, the proposed method outperformed for all evaluation metrics. The proposed method's accuracy was 1.8 and 4.3% higher than the Misra et al.'s and Doulah et al.'s methods, respectively.

When whole experimental results were considered, it is seen that the proposed method can be deduced as successful in detection of ALS disease. Converting the EMG signals into images based on the T–F transformations and combined the deep CNN architecture with reinforcement learning strategy constituted a robust approach.

Conclusions

In this paper, a new scheme was proposed to classify ALS diseases based on convolutional neural network using EMG signals. To this end, three T–F representation methods have been used to convert the 1-D EMG signals into 2-D T–F images. These images contain rich texture information which is useful for discrimination of the ALS and healthy persons. CNN can extract this rich texture information with its filters and classify them with embedded classifier. We conducted extensive experiments and the obtained results showed high accuracy. We further extracted various texture features and used various classifiers for comparison purposes. In addition, some published results on the same dataset were used for comparison. For all comparisons, we proposed method outperformed. In the future works, we plan to construct more deep CNN architectures for improving the accuracy. Moreover, various T–F representation methods will be used in future works.

Table 1 Performance comparison with other methods

T–F method	Sensitivity (%)	Specificity (%)	Accuracy (%)
SPWVD	99.71	75.37	81.92
Spectrogram	94.24	97.59	96.69
CWT	94.80	98.80	96.80

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