표면 근전도를 이용한 순환 신경망 기반의 손동작 분류

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Abstract

In this paper, we proposed an sEMG classification method with recurrent neural networks. The proposed method was evaluated using Ninapro dataset. The classification results were compared with classical methods and CNN using same dataset. A model ensemble with various time step was applied to improve the performance. In addition, we experiment with the time window size. As a result, it shows an improvement of about 8.8% and 17.5% in average classification accuracy compared to the classical methods and CNN respectively. This result demonstrates that our proposed method using RNN can be effectively used for sEMG classification.

1. Introduction

Despite the advances of modern technology, trans-radial amputees still have many inconveniences in their behavior. Patients suffering from neuromuscular disorders are also being constrained in many parts of their lives. The muscles of patients with the neuromuscular disorder are not functioning properly due to disease of voluntary muscles, nerves, and neuromuscular junctions. So to assist them, there are many modern prosthetic devices for these patients, but they do not provide enough satisfactory performance.

There have been many studies on prosthetic devices to address these problems. In recent years, mechanically advanced prosthetic devices have appeared. However, the method to control such advanced devices requires much development. Controlling the devices is not a natural motion, and the user can only control the devices by a predetermined method and it requires a lot of training.

Therefore, there are studies to control the prosthesis through biosignals such as EEG and EMG[1][2][3]. However, the research in this field is also experiencing a lot of difficulties and is not showing the applicable performance in practice.

Recent achievements of deep learning show the possibility of solving these problems. Deep learning has achieved remarkable results in many fields, especially in the areas of computer vision and natural language processing. The most successful examples of deep learning architectures are convolutional neural network and recurrent neural network. As a result of these recent developments, deep learning was applied to EEG classification[4] and EMG classification.[5]

In this paper, we propose an sEMG classification method using a recurrent neural network. We also improved the performance through the model ensemble, which shows better results than classical classification methods and CNN.

In all our experiments, we trained and verified our method with Ninapro dataset.[6] The Ninapro dataset includes sEMG datasets which were recorded from intact subjects and trans-radial subjects and released for studying the relationship between sEMG and hand movements.

This paper is organized as follows. In Section 2, our method is described. Section 3 described the dataset and experiment settings. And Section 4 demonstrates the experimental results. Finally, Section 5 concludes the paper.

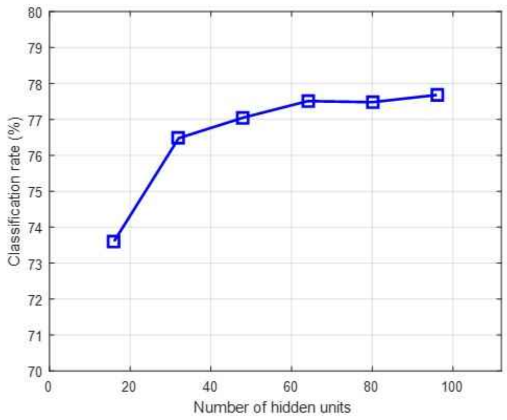

Figure 1. Performance of sEMG classification for different number of hidden units in recurrent units

2. Method

We applied recurrent neural networks to deal with multiple channel sEMG data. sEMG dataset was divided into overlapping time window along the time axis. Each time step of the time window was input to RNN unit. Then, softmax layer was applied to the output of the last RNN unit to obtain the probability for each class and the class for each window was determined.

In addition, we improved performance through a model ensemble with various time steps. For each RNN model, a different number of Sequential time steps were concatenated and used as input to RNN unit. The output of each model is summed and softmax is applied to determined class.

3. Experiment

3.1 Dataset

The proposed method was trained and verified using the Ninapro dataset. Ninapro dataset includes surface electromyography data measured from hand movements of 79 subjects.

Ninapro dataset consists of three sub datasets(Database1, Database2, Database3). In this paper, we have experimented with Database 1. Database1 includes sEMG recordings for 52 hand movements measured from 27 intact subjects.

Table 1. Average Classification rates for Ninapro dataset(Database 1)

method	Acc.
Random Forest[6]	66.59%
CNN[5]	75.32%
RNN(200ms)	77.51%
RNN(Ensemble,200ms)	80.82%
RNN(Ensemble,300ms)	82.01%
RNN(Ensemble,400ms)	82.88%
RNN(Ensemble,500ms)	84.13%

Each hand movements are repeated 10 times and each movement repetition lasted 5s. The rest posture lasts for 3s and is applied between each movement repetition. There are 10 channels which correspond to each sEMG electrode. The sampling rate is 100Hz.

3.2 Experimental settings and data preparation

The size of the window is 200ms as in [6], so there are 20-time steps per window. The stride of the time window is set to 1-time step for both training set and test set. The class of each time window is determined as the class that covers more than half of each window. There was no data preprocessing except zero mean normalization. As in [6], repetition 2,5 and 7 were used for the test set while the remaining repetition used for the training set.

4. Result

First, We searched the appropriate values of the hyper-parameter of a recurrent convolutional neural network. There are various recurrent units such as LSTM, GRU, and MUT. We used GRU in our experiments. The number of hidden units was determined through grid search. Figure 1 shows classification results for a different number of hidden units. Since the result for 64 hidden units are the highest and converged performance of 77.51%, it is fixed as the values in the following experiments.

Next, We experimented with 5 models with 20, 10, 5, 4 and 2 time steps for a model ensemble. Table 1 shows the average classification rate of the RNN, CNN and classical method. In addition to this, we experimented with various time window size. As the size of the time window increased, the classification performance increased. Finally, the classification result was 84.13% with the model ensemble for a time window size of 500ms.

5. Conclusion

In this paper, we proposed an sEMG classification method with recurrent neural networks. We also applied model ensemble to improve performance by considering various sequential information. The proposed method was evaluated using Ninapro dataset.

It provides about 8.8% and 17.5% higher than classical method and CNN for the Ninapro dataset. These experimental results show that our proposed method can be effectively used for sEMG classification.

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