Surface Electromyography Signals based Recognition of Finger Number Gesture using Convolutional Neural Network

J. Park¹, C. Kwon¹

¹Department of Medical IT Engineering, Soonchunhyang University, Asan, ChungNam, Korea

Abstract – This work deals with the application of Convolutional Neural Network (CNN) to recognition of finger number gestures using time series sEMG signals as input rather than visual images. It investigates CNN’s performance in recognition of sEMG based finger number gestures, which has been not studied in the literature. To the end, 252 sEMG signals as input data and 108 sEMG signals as test data were acquired from the 4 electrodes on a forearm muscle of a subject who is well-trained to make consistent performance of six Korean finger number from zero(0) to five(5) selected for this study. With the sEMG data of six Korean finger number gestures, CNN is set to have 100 steps of learning to recognize six Korean finger number gestures. This work will show recognition rate at each learning step to show CNN’s learning ability in the application to recognition of time-series based finger number gesture.

Keywords: convolutional neural network, time-series surface electromyography signals, finger number gesture recognition,

1 Introduction

Unlike the classical classification approaches, a Convolutional Neural Network (CNN) as one of learning algorithm is the approach to learn useful features directly from raw image data and performs automatic classification for the given task. This indicates no need to find hand-crafted feature extraction and classification any more [1]. Recently researchers turn their attention to a convolutional neural network (CNN) as an alternate solution for image recognition. Recently researchers turn their attention to a convolutional neural network (CNN) as an alternate solution for image recognition. CNN has demonstrated excellent performance for static 2D images [2] and successfully extended itself to other non-static domains such as sentence classification [3].

As the research has shown that CNNs can outperform classical hand-crafted approaches in various domains, we may expect that CNNs can also learn useful features from raw sEMG sensor data obtained during performance of Korean finger number gestures and outperform classical classification approaches.

Regarding the research direction of multiple finger gesture classification, to our knowledge, relatively few research papers based on CNN using sEMG signal data were published and there was no such multiple finger gesture related work proposed yet. In this work, we implement a CNN based multi-finger gesture recognition system using sEMG signal data and investigate the CNN’s feasibility in its application to multi-finger gesture recognition system.

This work demonstrates CNN’s outstanding performance as a preliminary study for possible practical applications. To this end, six Korean finger number gestures from zero to five are selected and illustrated in Fig. 1.

Figure 1. Six Korean finger number gestures for CNN based recognition

2 Materials and methodology

2.1 sEMG system

The sEMG system used in this work is Active-II system which is developed for research applications only by Biosemi Inc, in Netherland. This system can have max 280-channel, DC amplifier, 24-bit resolution of ADC, and biopotential measurement system with Active Electrodes.

2.2 Experimental setup

One healthy subject who is well trained to take finger number gestures volunteered for this study. We used the 4-Channel sEMG system. TABLE I Relations between electrode pairs and muscles selected

<table>
<thead>
<tr>
<th>Muscles Selected</th>
<th>Flexor digitorum superficialis</th>
<th>Flexor Pollicis longus</th>
<th>Abductor Pollicis longus</th>
<th>Extensor digitorum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electrode Channel</td>
<td>CH1</td>
<td>CH2</td>
<td>CH3</td>
<td>CH4</td>
</tr>
</tbody>
</table>

channels from multiple channels to collect sEMG signals from the subject by flat-type active electrodes as listed in Table 1 [4]. The time-series raw data when finger number gestures are performed are obtained with a 1024 Hz sampling rate.

The subject sat in a comfortable chair and naturally performed six Korean finger number gesture movements. Each movement lasted for about 1s and the time interval between two adjacent movements was about 1s. For each of the 6 finger number gestures in the set, we collected 20 trials from the subject to provide enough data samples for training and classification. All sEMG data were collected within one session. This procedure is demonstrated in Fig. 2. The subject completed the three separate sessions with the time interval of about 5 minutes between two adjacent sessions. As a result, 252 sEMG signals as input data and 108 sEMG signals as test data were acquired from the 4 electrodes on a forearm muscle of a subject who is well-trained to make consistent performance of six Korean finger number from zero(0) to five(5) selected for this study.

To arrange time-series sEMG signals for use of Tensor-flow software tool which runs CNN, rectification of the raw sEMG signals are performed by taking absolute value and the rectified sEMG signals are rounded to the nearest whole number. Final sEMG input data to Tensor flow software tool are obtained by scaling them by 10 times

Figure 2. Timing diagram of 20 trails for each finger number gesture in one set

2.3 Convolutional Neural Network

There are several hyperparameters to be chosen for the CNN architecture; depth and width of the CNN architecture, convolution and pooling window sizes, their stride sizes, activation functions, etc. The baseline CNN architecture that is used for the experiments is presented in Fig. 7. In the baseline CNN architecture, two convolution layers, which have 32 and 64 feature maps, are followed by a fully connected layer which has 1024 nodes. Rectified units [5] are employed as activation functions and softmax functions are used for evaluating the final 6 output node values. The effects of different CNN architectures is left for future research. With the sEMG data of six Korean finger number gestures, CNN is set to have 100 steps of learning to recognize six Korean finger number gestures.

Figure 3. The baseline CNN architecture has two convolutional layers followed by a fully connected layer

3 Conclusions

This paper will investigate the feasibility of CNN in the application to sEMG based recognition of finger number gestures by showing that six Korean finger number gestures are classified.

The expected advantage in use of CNN to recognize Korean finger number gesture recognition using sEMG signal data is to get rid of any hassle to choose a suitable feature extraction technique and classifier since CNN itself does same procedure automatically by learning features from raw sEMG data. If CNN is observed to do excellent performance in this work, we may believe the CNN is promising solution for practical applications such as human–computer interaction (HCI) using sEMG data

4 References