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Recognition of Composite Motions based on sEMG via Deep Learning

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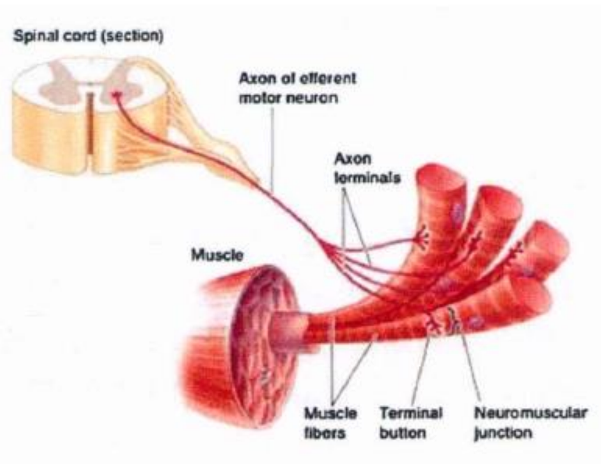
Part.01

Introduction

1.1 sEMG signal



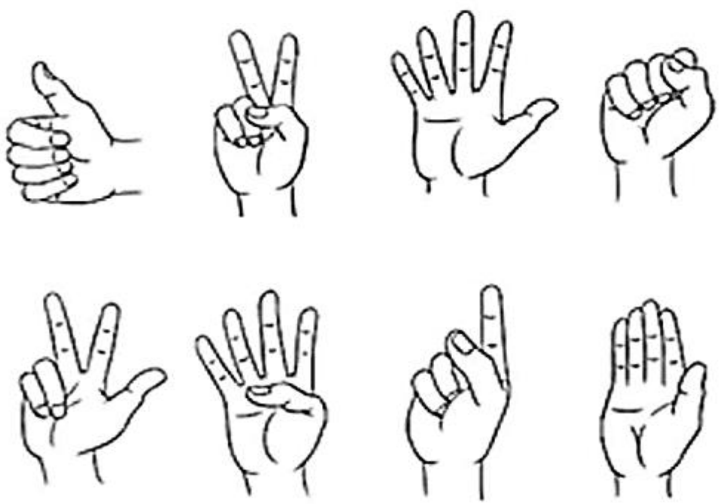
Needle Electrode

Surface Electrode

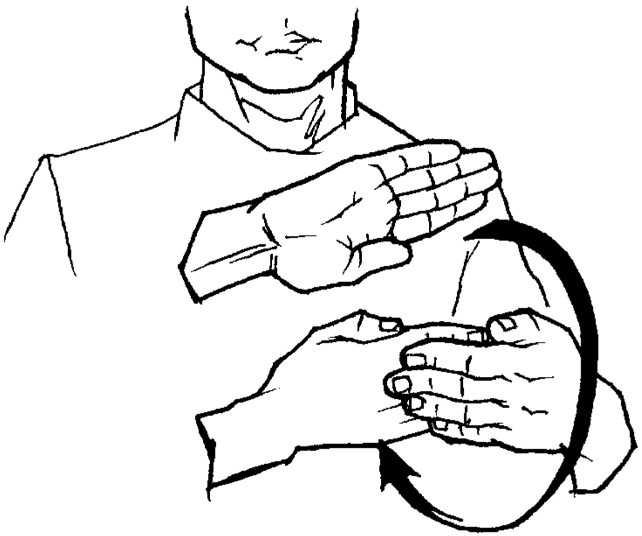
Advantages of Motion Recognition based on surface electromyography (sEMG):

- Convenient operation
- Non-invasion to bodies
- Noninterference on motions

1.2 Composite Motion



Simple motions



Composite Motions

According to the change of the motion, motion can be classified into two types:

- Simple motion: instantaneous gesture
- Composite motion: motion will changes in the interval of sampling, such as sign language motion and handwriting motions.

1.3 Review

Simple Motion

Conventional Methods

- Focus on various combination of features and classifiers.
- Limitation leads to low accuracy and weak generalization ability

Deep Learning

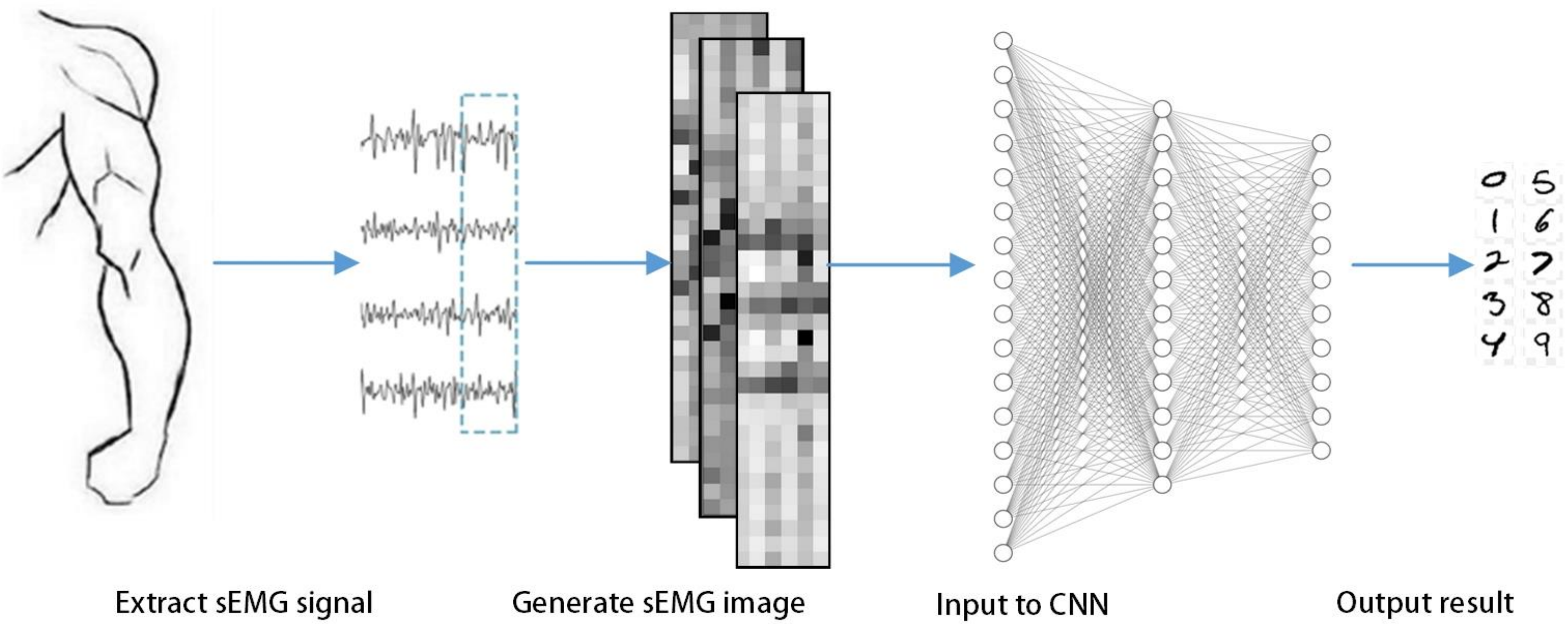
- Novel concept: "sEMG Image”
- A very simple CNN architecture can produce more accurate results.

Composite Motion

- No methods for general composite motion.
- Few researches rely solely on sENG.
- Base on the complex and abstract models.

Could we achieve a simple and general method via deep learning to recognize composite motions like the way of processing image?

1.4 The proposed method



In this study:

- Defined a new “sEMG Image” concept.
- Established a Convolutional Neural Network (CNN).
- Utilized the pre-training by irrelevant data set to optimize the method.
- Tested this method on two different recognition tasks of composite motions.

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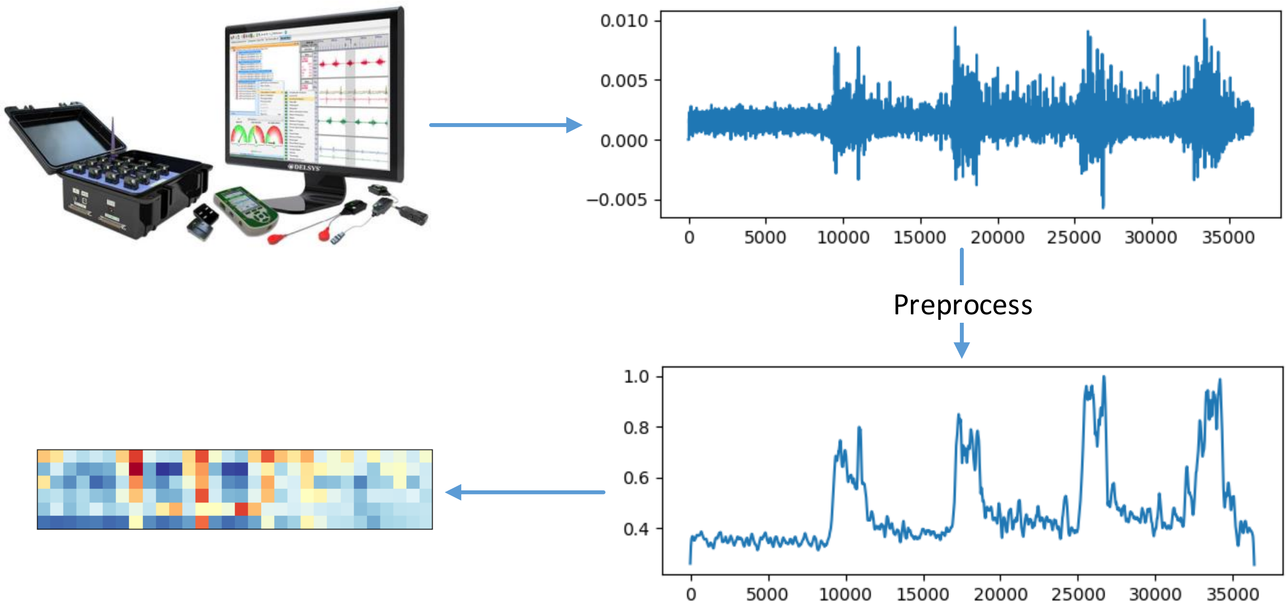
Part.02

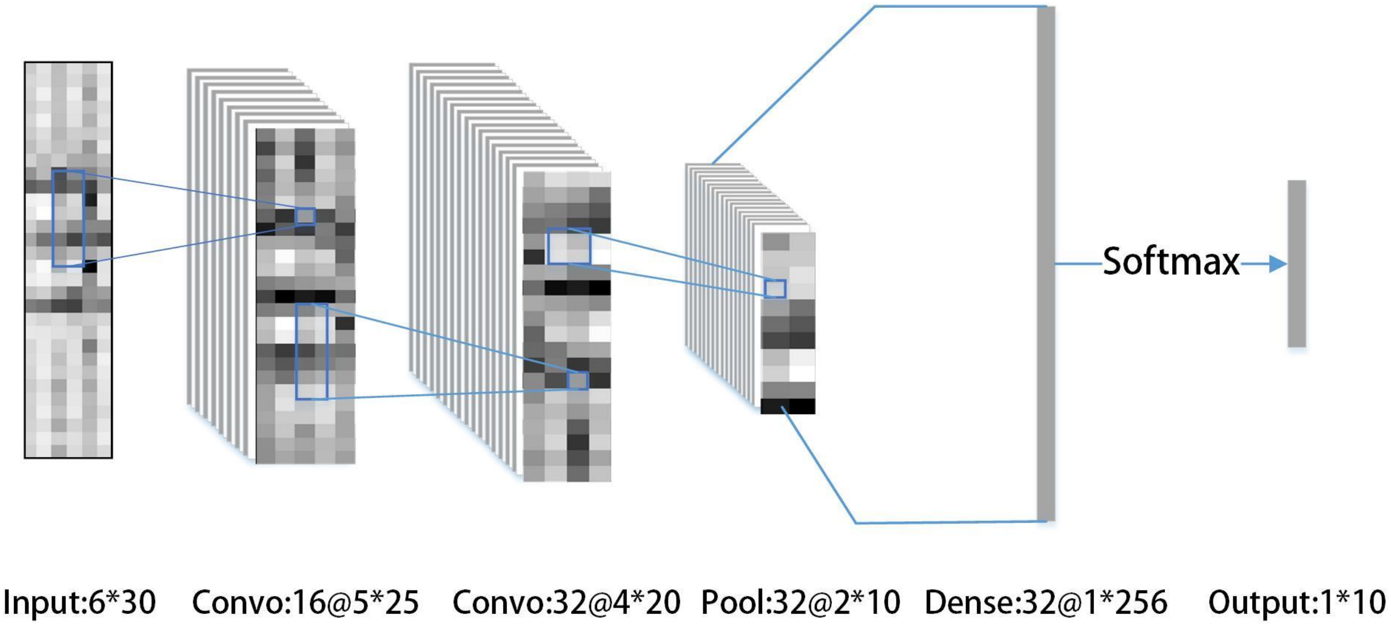
Method

2.1 sEMG Image



- Preprocessing: band-pass filtering, rectification and nonlinear normalization.
- A new sEMG Image:
  - Each pixel of sEMG images represents the activation degree of corresponding electrode at a certain time.
  - Texture features of sEMG image can reflect correlations between muscles activation and time sequence.

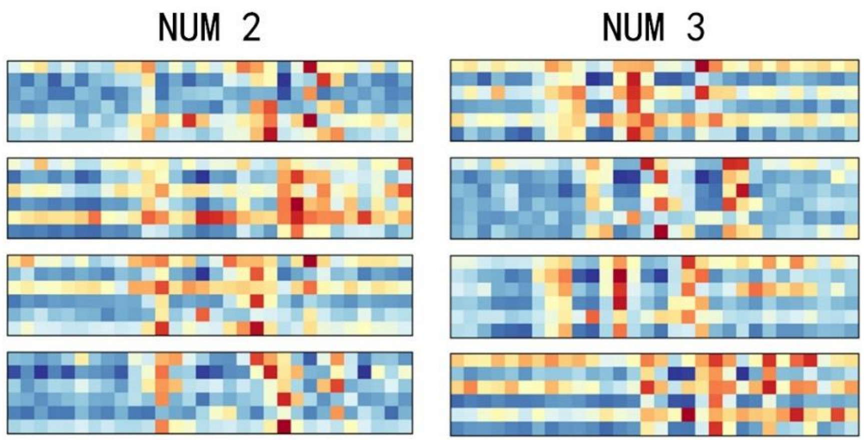
2.2 Convolutional Neural Network



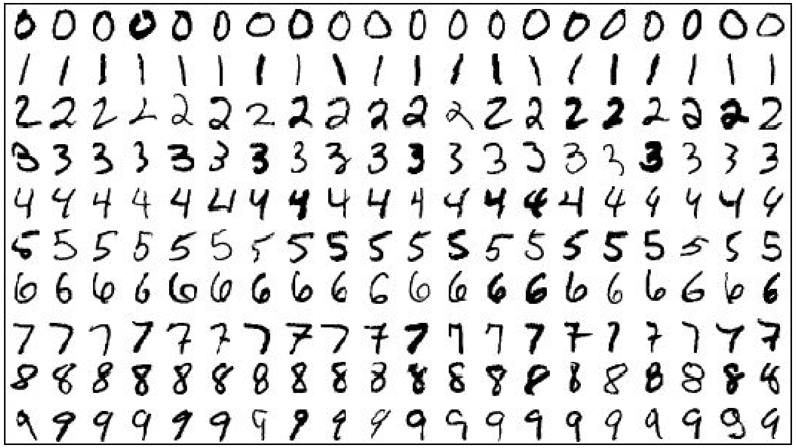
The advantages of CNN:

- Convolutional filters can help extract effective features from sEMG image instead of designed by experts.
- Scale and translation invariance can contribute to strong generalization ability of the recognition method.

2.3 Transfer Learning



sEMG images



MNIST data set

In order to acquire effective convolutional filters to process texture information, we propose to pre-train the network by MNIST. The steps of Fine-tuning:

- Save the weight values of the network pre-trained by the MNIST.
- Based on the pre-training, fix the weight values of the convolutional layers and train the fully-connected layer with the sEMG images.

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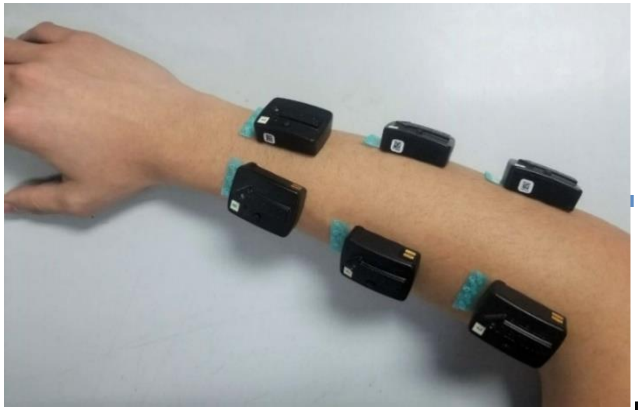
Part.03

Experiment

3.1 Handwriting Number



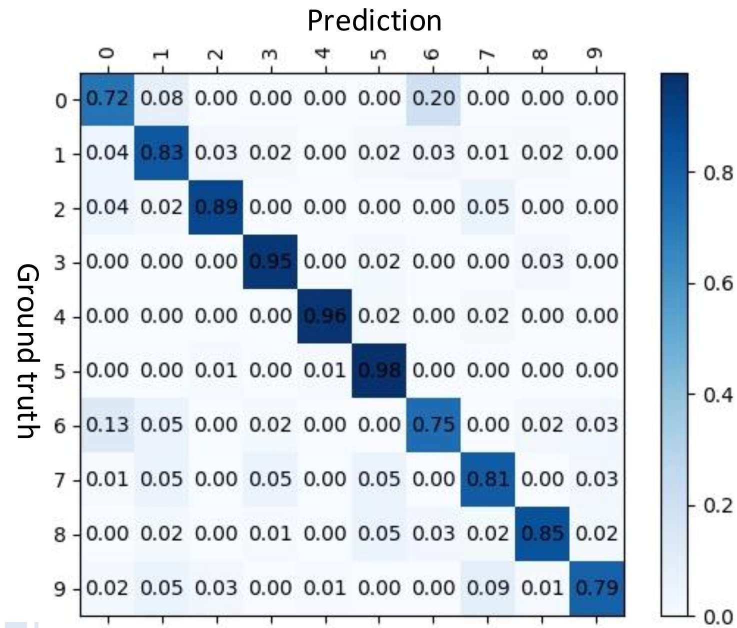
Positions of Electrodes

Process of Data Collection

3.1 Handwriting Number

TABLE I
THE HANDWRITTEN RECOGNITION EXPERIMENT

Method	Same Size		Different Size	
	Train Acc	Test Acc	Train Acc	Test Acc
SVM	0.42	0.31	0.34	0.26
DTW	0.87	0.76	0.62	0.47
CNN	0.95	0.79	0.83	0.72
TransL	0.96	0.83	0.85	0.75



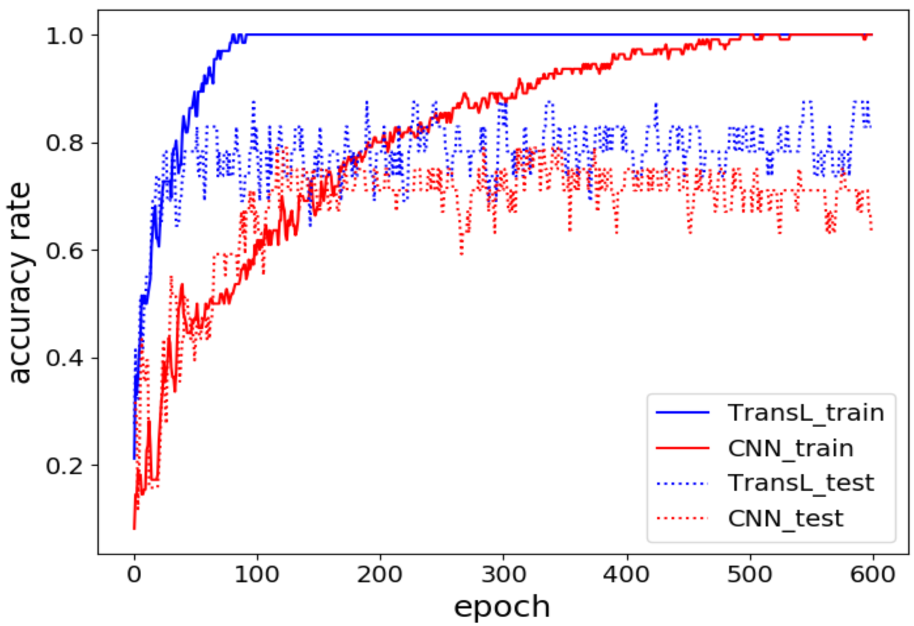
Left Table:

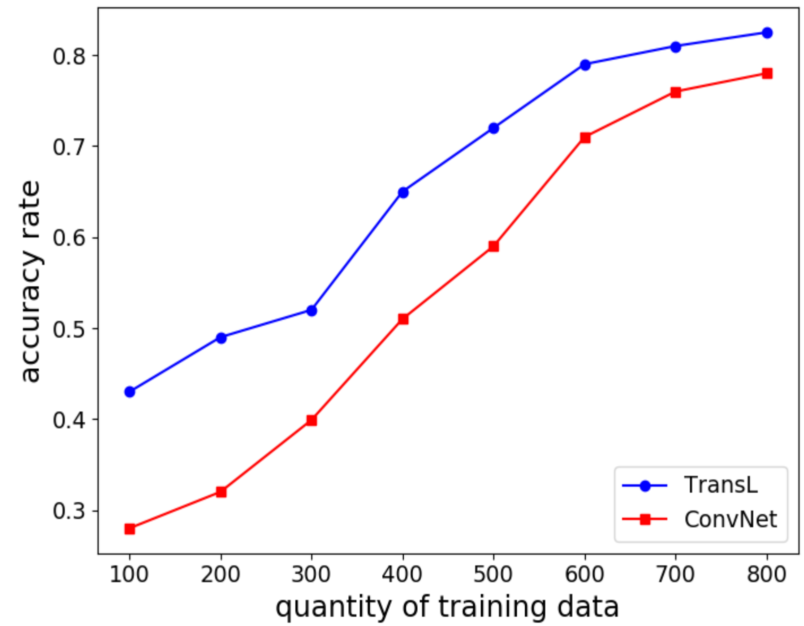
- Support Vector Machine (SVM) is not effective.
- Accuracy of Dynamic Time Warping (DTW) was greatly reduced in experiments of different size numbers.
- Raw CNN and pre-trained CNN performed well in both experiments.

Confusion Matrix:

- Accuracies of numbers 3, 4 and 5 were very high, while 0 and 6 were easily confused with each other.

3.1 Handwriting Number

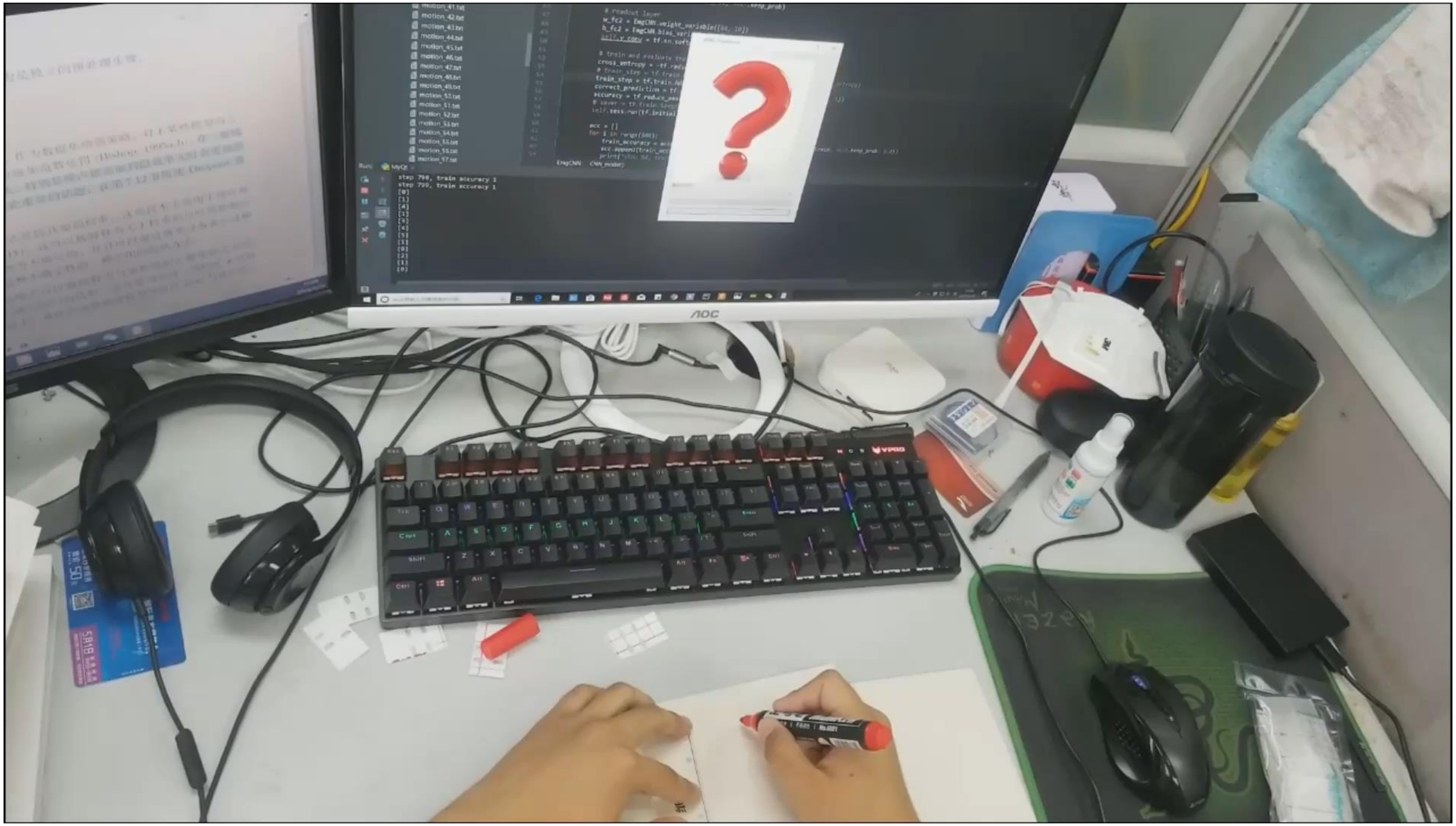




The analysis of results:

- Convergence of transfer learning method is faster, and its performance is better.
- Based on same size of training data, The transfer leaning performs better than CNN.

3.1 Handwriting Number



3.2 Sign Language

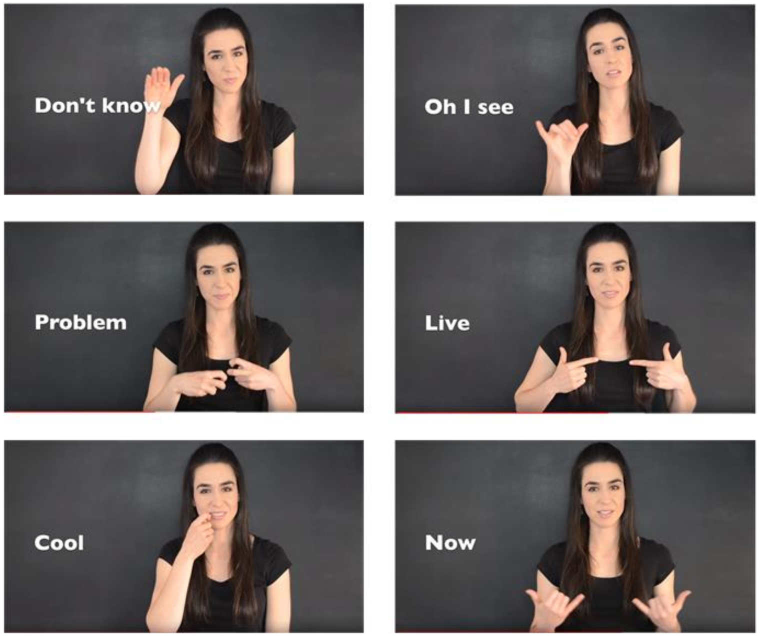


TABLE II

SIGN LANGUAGE EXPERIMENT

Method	Train Acc	Test Acc
CNN	0.95	0.79
TraL	0.96	0.82

- 20 signs of American Sign Language (ASL)
- The accuracies in the right table demonstrate again the effectiveness of the proposed method.

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Part.04

Conclusion

In this paper, we proposed a novel method that applies CNN to process sEMG signals like the way of processing images and achieves accurate recognition for general composite motions. The main contribution of this paper is summarized as follows:

- Defined a new "sEMG Image", which can represent general composite motion and reflect the correlation between muscular activations and time sequence.
- Established a simple CNN architecture, which can achieve higher precision and stronger generalization ability than conventional methods.
- Pre-trained the network by MNIST, which can help the proposed method to speed up convergence and reduce the demand for data.

This method is simple, general and also effective!

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Thanks for your listening!