sEMG – based Hand Gesture Recognition

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Abstract

This Msc Thesis is focused on the development of the architectures of convolutional neural networks for the recognition of hand movements through surface electromuscular signals. For the needs of this work, datasets DB1 and DB5 from Ninapro and DB-c from CapgMyo were selected. For each of them, processing techniques such as filtering, amplitude normalization and sEMG image creation are implemented. Furthermore, two experimental stages of the present study follow. The first stage outlines the creation of the neural networks, the process of selecting hyperparameters, but also the results of movement classification for each database. In the second stage, a study is performed on CapgMyo's DB-c dataset, to identify the group of electrodes which is the most important in motion recognition. Thus, data of each group of sensors is altered in two ways. First, recordings are replaced with zero values and then with random noise values. Finally, classification results are listed for each case and conclusions are summarized.

Introduction

Daily life of humans is intertwined with the use of their hands. Human hands allow individuals to interact with their environment and complete a wide range of tasks and activities. However, due to accidents or diseases some people have lost their upper limbs or parts of them.

Scientific community has contributed to the development of hand prosthetics and continues to seek ways to help people with upper limb disabilities.

In the field of Human Computer Interaction, there has been particular interest in designing interfaces that will allow the computer to recognize the movement the user wishes to perform. The connection between the desired movement and the device which will execute it, is the electromuscular activity.

When performing a movement, the muscles contract and dilate, producing electrical signals. These signals can be easily recorded with the help of surface electromyography. Surface Electromyography (sEMG) is a non-invasive method that allows the recording of the electrical activity of the muscle fibers during the execution of movements.

The rapid development of artificial intelligence and especially Deep Learning, has led to impressive results in a variety of research fields. Therefore, it was a matter of time to be used in the recognition of upper limb movements and the control of prosthetic hands.

The sEMG-based gesture recognition with deep learning approach plays an increasingly important role in human-computer interaction.

Wanting to contribute to this effort, we developed neural network architectures, for three publicly available sEMG datasets, which classify various hand and finger movements. Furthermore, we investigated the impact on recognition accuracy when altering emg recordings with zero and noise values.

Methods and Materials

For the purposes of this work, we trained the networks to recognize 52 gestures from datasets DB1 and DB5 of Ninapro database and 12 gestures from dataset DB-c of CapgMyo. For the Ninapro datasets we perform intra subject classification and we calculate the mean accuracies. The process we followed and the architectures of the networks we created are shown in the following figures.

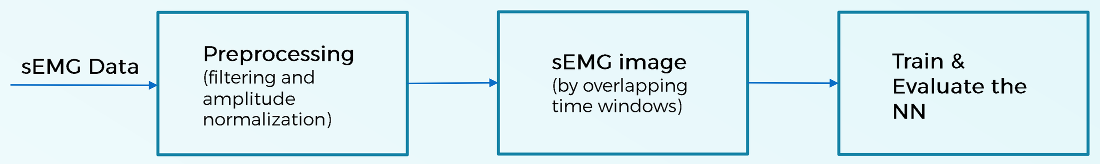

Figure 1: Block diagram of the process.

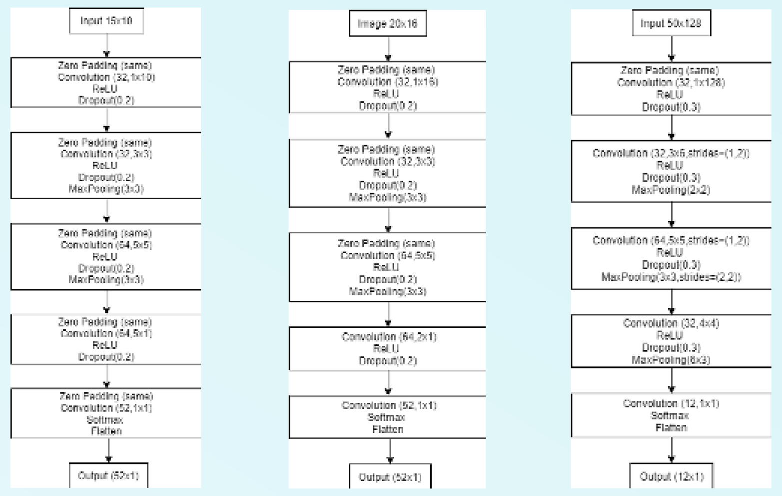

Figure 2: Neural network architectures (structures from left to right – DB1, DB5, Db-c).

Results

Part A: Hand Gesture Classification

Table 1: Classification accuracies (for DB1 and DB5 values refer to mean accuracy and standard deviation of volunteers' results).

	DB1	DB5	DB-c
Test accuracy	68.17 % ± 6.12 %	55.05% ± 3.96%.	87.31 %

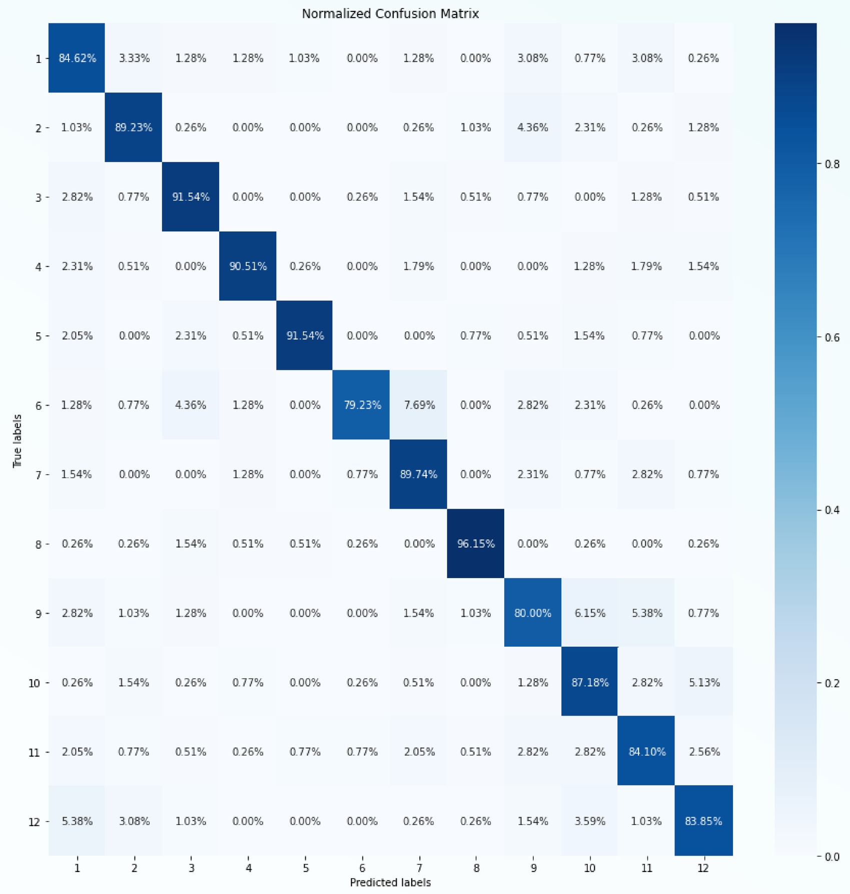

Figure 3: Normalized confusion matrix of 12 gestures of dataset DB-c.

Part B: Replace data with zeros and noise

In this part, we studied the effect of alteration of electromuscular signal data on motion recognition. More specifically, for each one of the 8 teams of electrodes used to record the DB-c dataset we replace its data in two ways. At first, we replace its values with zeros and secondly, with random noise values. Then we train and evaluate the network with the modified data. Results for each case are shown in tables below.

Table 2: Classification results for replacing data with zero values.

Team with Zeros	Electrodes	Epochs (/30)	Training Accuracy (%)	Training Loss	Validation Accuracy (%)	Validation Loss	Test Accuracy (%)	Test Loss
1	[1:16]	24	80.19	0.5712	79.42	0.8198	78.97	0.812
2	**[17:32]**	**20**	**76.44**	**0.6800**	**73.97**	**0.9389**	**74.19**	**0.9216**
3	[33:48]	30	77.59	0.6335	75.97	0.8288	78.42	0.7841
4	[49:64]	30	77.91	0.6349	76.37	0.8424	78.23	0.8174
5	[65:80]	18	80.14	0.5687	77.41	0.8005	77.33	0.7892
6	[81:96]	29	83.47	0.4768	82.07	0.6597	83.10	0.6403
7	[97:112]	16	79.53	0.5906	78.15	0.8034	79.04	0.7858
8	[113:128]	27	85.21	0.4290	82.50	0.6154	83.95	0.5862
Ground truth	All available	30	86.20	0.5562	85.59	0.5856	87.31	0.5562

Table 3: Classification results for replacing data with random noise values.

Team with Noise	Electrodes	Epochs (/30)	Training Accuracy (%)	Training Loss	Validation Accuracy (%)	Validation Loss	Test Accuracy (%)	Test Loss
1	[1:16]	19	79.64	0.5942	77.17	0.8062	78.5	0.7728
2	**[17:32]**	**22**	**75.07**	**0.7224**	**73.23**	**0.9378**	**74.08**	**0.9061**
3	**[33:48]**	**27**	**76.78**	**0.6712**	**73.58**	**0.9119**	**74.27**	**0.9038**
4	[49:64]	23	78.34	0.6191	74.47	0.8834	75.02	0.8765
5	[65:80]	29	82.71	0.499	79.24	0.7197	78.63	0.7215
6	[81:96]	26	79.95	0.5734	78.65	0.7692	81.22	0.7227
7	[97:112]	30	85.32	0.4257	81.42	0.6165	81.42	0.6162
8	[113:128]	24	81.96	0.5178	80.14	0.7469	80.81	0.7325
Ground truth	All available	30	86.2	0.5562	85.59	0.5856	87.31	0.5562

Conclusion

In this study we developed three network architectures to classify hand gestures through sEMG signals. For the first part, we achieved results similar to those of the international literature. The best results were achieved for dataset DB-c of CapgMyo database, possibly due to its small number of movements to be recognized and its high-density EMG data. For the second part, we reached the conclusion that both approaches, replacement of data with zeros and random noise, agree that the second team (electrodes [17:32]) is the most important in the classification.

Future Directions

- Try another method of creating sEMG images, such as frequency transformations or spectrogram.
- Modify the structure of the network and perform classification with all available data for Ninapro datasets.
- Use or RNNs instead of CNNs.

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References

1. M. Atzori, M. Cognolato and H. Müller, "Deep learning with convolutional neural networks applied to electromyography data: A resource for the classification of movements for prosthetic hands", *Frontiers Neurorobot.*, vol. 10, pp. 9, 2016.
2. W. Geng, Y. Du, W. Jin, W. Wei, Y. Hu, J. Li, "Gesture recognition by instantaneous surface emg images", Sci. Rep., 6 (2016), p. 36571.
3. Y. Du, W. Jin, W. Wei, Y. Hu and W. Geng, "Surface emg-based inter-session gesture recognition enhanced by deep domain adaptation", *Sensors*, vol. 17, no. 3, pp. 458, 2017.

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