sEMG Based Control: a Deep Learning Approach

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Abstract

This Msc Thesis investigates the use of surface electromuscular signals as control signals in an attempt to implement a real – time simulation using deep learning techniques. A suitable CNN architecture is developed with Python's keras library and trained in Google Colab, using the DB5 dataset of the NinaPro database. Furthermore, a control protocol is created, which exploits sequences of movements with high accuracy to achieve mapping to more functions of the application. This method suggests that even with a small number of distinct movements, there is a way to achieve high quality control.

Introduction

The use of surface electromuscular signals has led to significant results the past few years, mainly in the field of hand prosthetics.

However, the existence of only a few, small databases, prevents researchers from developing models that achieve high accuracy results for a lot of different movements.

At the same time, existing methods are based on repeating the movement as long as the user desires the same result. This can lead to exhaustion faster and, as a result, to more noisy data, thus more errors.

This thesis proposes another method for tackling this complex problem. On one hand, it introduces a protocol that helps in cases where there is lack of data, by achieving better results on the already existing ones, while on the other hand, it suggests an overall more relaxed way in order to perform movements in sEMG based applications. Additionally, this method makes it possible to use more of the application's functions than the existing movements, as it is based in sequences.

Methods and Materials

For the purposes of this method, 3 movements where used from the set of 52 gestures that where contained in the 5th dataset of NinaPro. These 3 movements were used as vocabulary in order to create words (or chains). A CNN architecture was trained to recognize them.

Table 1. Mapping of movements to their code names.

Movement Name	Code Name
Fingers flexed in a fist	0
Wrist Flexion	1
Wrist Extension	2

Additionally, a movement was used given the name **Indicator Movement**, which signals the moment the user wants to give a command to the system. In this case, that movement was "Thumb Up". Another CNN model predicts when the user executes the indicator movement.

Table 2. Coding techniques.

Function	Uniform Coding	Huffman Coding
1	00	0
2	01	1
3	02	20
4	10	21
5	11	220
6	12	221
7	20	2220
8	21	2221
9	22	22220

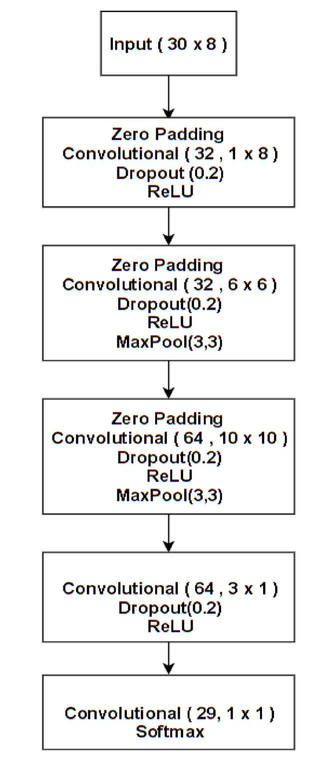


Figure 1. CNNs' Architecture.

Figure 2. Block diagram of the method.

Results

The developed protocol shows higher results than the traditional method, even in people whose data are not included in the database used for training the model.

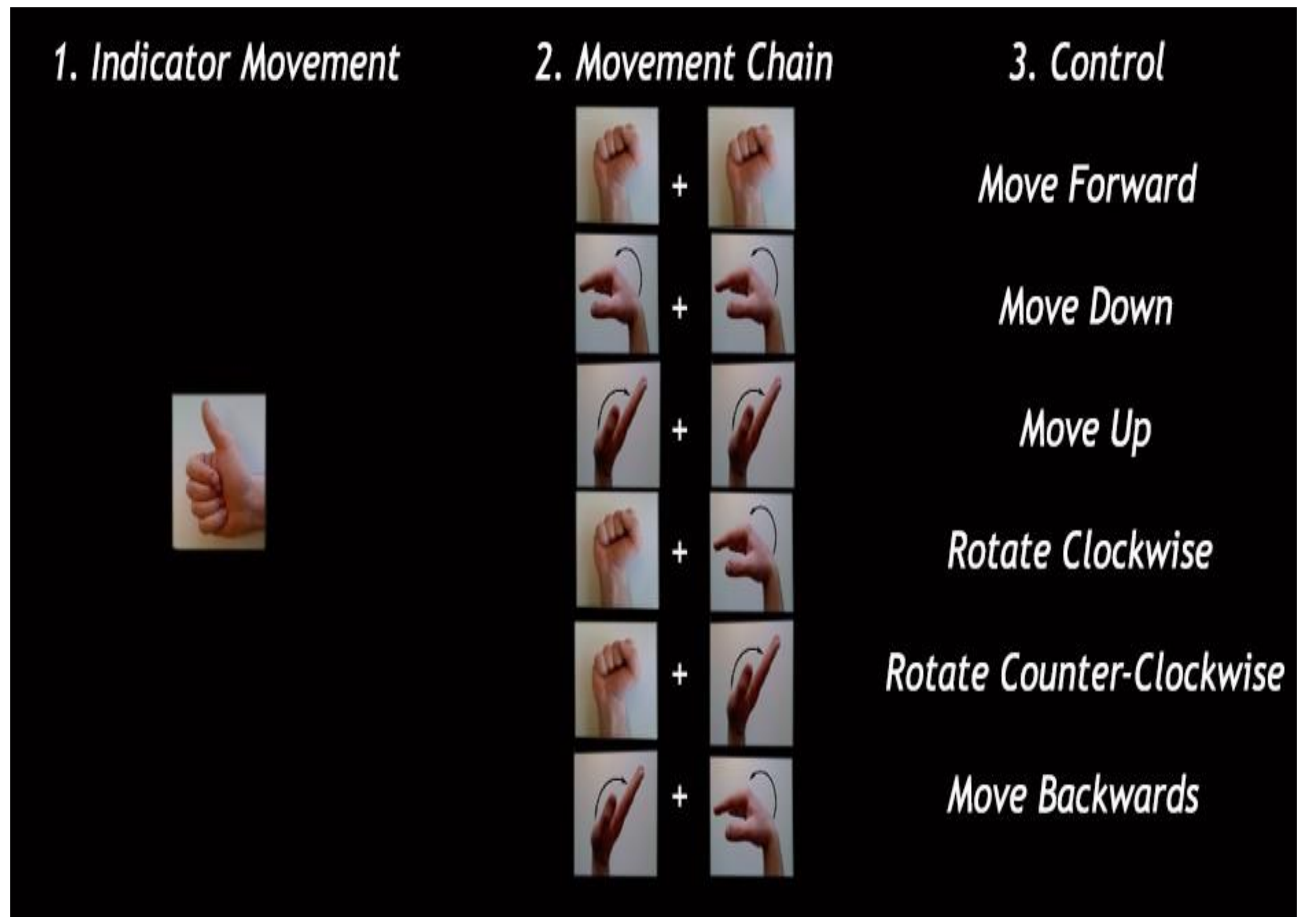
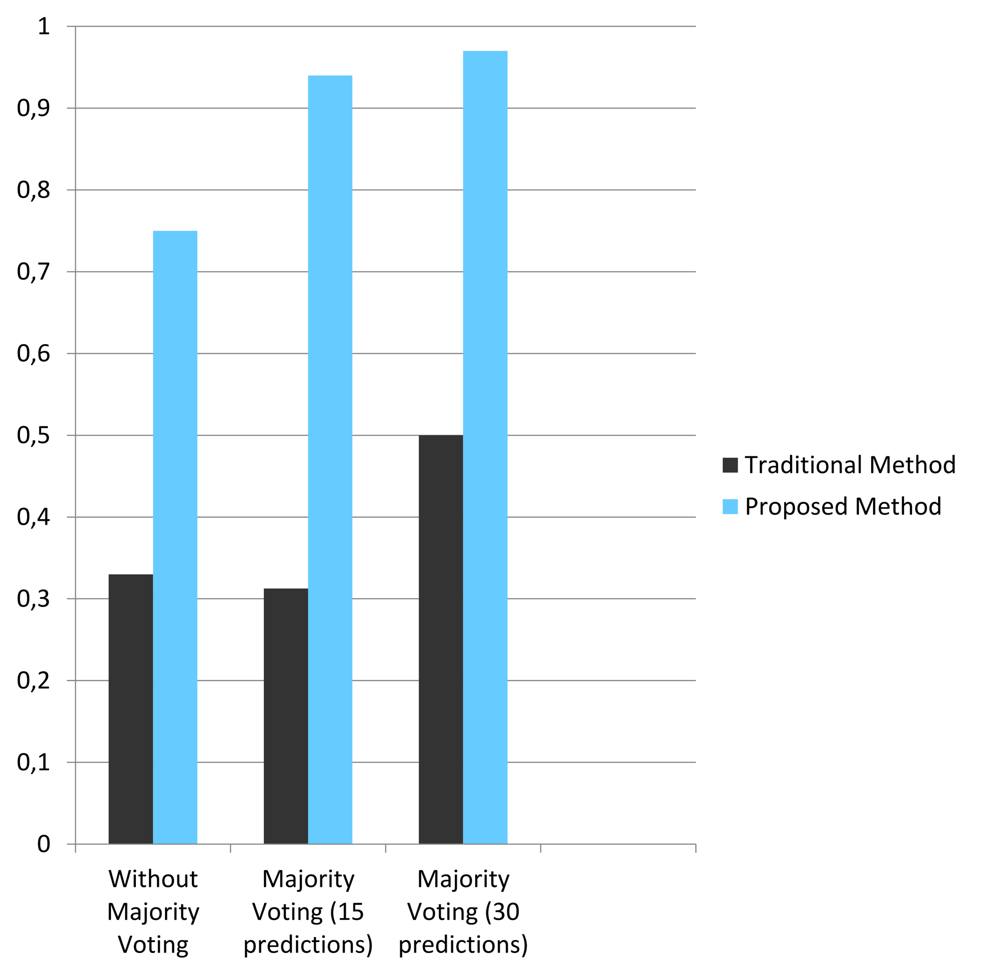


Figure 3. Steps of the Movement Chain method.

Chart 1. Mean accuracy of the 2 methods for the same subject .



Discussion

Benefits of the method :

- Faster
- Less exhausting
- Versatile (chain to function mapping can vary, according to the preferences of the user)

As in other sEMG methods, the user needs to learn the protocol of each movement. In this case, however, the burden is not learning how to execute the amount of different movements, because there are only a few, but to remember the combinations between them.

Conclusions

This study developed a method that maps movement sequences to an application's functions, in order to achieve high accuracy control. By using a Convolutional Neural Network, trained in specific highly independent movements, and by creating a protocol that utilizes it, a real time simulation was implemented, thus proving the efficiency of the proposed method.

Future Directions

Future work would contain an effort to extend this method to people who have experienced loss of their upper limb, as its successful results would be a way to expand their capabilities. Furthermore, there is interest in the development of a more compact application, which would make it easier for people to operate. Finally, the creation of a larger database would lead to better results, as well as the use of higher frequency sensors. Should the chance arise, experiments would be made to ensure potential improvements, by using better equipment.

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