Electromyography-based Hand Gesture Recognition System

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Abstract. Electromyography (EMG) is the bio-signal generated in muscles during their activities. EMG is used by clinicians to examine and diagnose the muscles activity, for commanding myo-prosthesis to help amputees overcome their disabilities as well as for human machine interaction applications. These fascinating applications require the classification of the EMG signals into categories depending on the targeted application. In this paper, we tackle hand gesture recognition based on EMG signal, which may be used for different tasks. We design two deep convolutional neural networks, evaluate and compare their performances on the NinaPro dataset. The proposed models show interesting results.

Keywords: EMG · Deep learning · CNN 1D and 2D · Hand gesture recognition · hand prosthesis.

1 Introduction

The Electromyography (EMG) measures the electrical activity generated in the muscles during their contraction. At the hand muscles level, the EMG signal is the physical phenomenon associated with the hand gestures. These biomedical, electrical signals occurring in the muscles are exploited to understand the muscle's working principle.

In order to examine the muscle activity, the EMG data can be recorded either with invasive or non-invasive methods. Surface electromyography (sEMG) is a technique widely adopted in research and clinical settings that measures muscle's action potential from the skin's surface, contrary to invasive methods that require penetrating the skin to reach the muscle.

Nowadays, EMG signals are used in various medical domains, such as clinical and biomedical applications for diagnosis, and modern human-machine interaction. EMG data can help amputees by exploiting these signals to build an efficient myoelectric prosthesis. EMG signals are also employed by clinicians for diagnosing neuromuscular diseases [15].

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The increased worldwide number of hand-imputed persons, due to accidents, war, or people born handicapped, has particularly attracted research and industry to come with solutions to help this category overcome their daily impediments. This is achieved through exploiting the EMG physiological signal to control artificial prostheses. In the last decade, most of these systems were powered by low precision sensors, that affect the recorded signal quality, and conventional machine learning algorithms such as k-NN, SVM and decision trees [5, 9, 13]. However, the development of the technology in terms of sensors, robotics, 3D printing, and the new techniques of artificial intelligence help scientists improve these systems. The improvement is seen in the performance accuracy of the prosthesis with more movements and functionalities.

This paper addresses the challenge of hand gesture recognition using the Electromyography signals to help improve the daily life of amputees as well as for other tasks. Our work relies on convolutional neural networks, where we propose two different approaches and compare their performances. The widely used NinaPro dataset [3] is exploited to evaluate the proposed approach.

The manuscript is structured as follows. In Section 2 we introduce various methods and systems of the state of the art. Section 3 provides the detail of the proposed method. Section 5 illustrates the evaluation results. Section 6 gives the conclusion with the future work.

2 Related Works

Various artificial intelligence algorithms have been applied to resolve the problem of EMG signal classification. The most investigated ones by the scientific community are the techniques based on machine learning, such as the traditional algorithms like, Support Vector Machines (SVM) [10, 14], Linear Discriminant Analysis (LDA) [5, 12], Random Forest (RF) [10] and Hidden Markov Model (HMM) [14]. For instance, Zhang et al. [19] used LDA classifiers and showed that their method provided acceptable performance in a noisy environment, where the obtained average accuracy was greater than 90 %. Moreover, Alfred et al. [1] tested and optimized three classifiers (SVM, HMM and DWT) while taking into consideration the noisiness of the data. Of these methods, the HMM classifier gave the highest accuracy while minimizing training and classification times.

In the light of several research studies, it has been observed that most researchers make feature extraction from EMG signals to apply a basic machine learning algorithm. These features are mainly designed for gesture recognition in time and frequency domains. On the other side, in order to allow researchers to establish better results in EMG classification, deep learning has attracted wide attention due to its powerful ability to handle a massive amount of data. For example, Zhang et al. [19] extracted 5-time domain features and used them to realize real-time gesture recognition based on ANN. Meanwhile Cote-Allard et al. [7] combined the frequency features of sEMG into a graph, and fed the graph to the CNN. Atzori et al. [4] designed a CNN architecture and compared it with classical classification methods by giving the same features, where the highest accuracy has been attributed to the CNN. Asif et al. [2] investigated the effect of hyper-parameters on each hand gesture in order to deliver a robust and stable hand gesture scheme for the deep learning approach. Geng et al. [8] introduced a deep CNN which outputs instantaneous prediction by giving the instantaneous values of EMGs, and proved that there is a spatial pattern of hand gestures hiding inside the instantaneous values of EMG.

Recently, transfer learning has shown to improve the prediction performance in the target domain. Therefore, Cote-Allard et al. [6] proposed inter-subject recognition by adopting Progressive Neural Network (PNN) performing transfer learning based on one repetition of seven gestures, and the target network achieved an average accuracy from 86.77% to 93.36%.

In this paper, we propose two convolutional neural network architectures for hand gesture recognition from EMG signals. Different from the literature works, our models operate on the EMG signals rather than extracting features before feeding the neural network. This aims to reduce the complexity of the system making it adequate to be embedded on the prosthesis.

3 Proposed Approach

In our approach, we directly introduce the EMG signal to the designed models as inputs, avoiding any extra feature extraction stage. Thus, the deep learning models' potential of learning from raw data is harnessed by our approach. In the following, we present our proposed system for hand gesture recognition.

3.1 Data Preparation and Pre-processing

The EMG signals should be divided into frames (windows) of identical sizes in order to be able to identify the different movements. In this study, the widow size is set to 150ms (giving 300 samples as the sampling frequency is 2KHZ). An overlapping of 50ms is taken between each two successive windows.

In the dataset, the gesture labels are attributed to each sampled point of the signal. As our system decides based on windows, to each window should correspond a unique label value. Therefore, we attributed to a given window the label whose occurrence is at least two-third of the window size.

Once the windowing is applied, we split the data into training and test subsets as follows.

- The first, second, fourth and sixth repetitions were selected as the training subset,
- The third and fifth repetitions were saved for the test subset.

After windowing and splitting the EMG data, we found the number of per-class samples to differ from one class to another with considerable margins leading to an unbalanced data classification problem. Therefore, we proceeded to balance our data by keeping the average number of samples for classes with larger sizes.

Finally, we re-scaled the EMG windowed signals by reducing the average μ of their values to 0 and the standard deviation σ to 1.

4 Proposed Neural Network Architectures

In our work, two architectures were designed, evaluated and tested to recognize fifteen hand movements by exploiting the raw EMG signals. After testing different neural network models and training setting, we selected the presented ones. Fig. 1 and 2 illustrates the proposed architectures retained in this paper. The two architectures are described below.

4.1 CNN-1D Model

One-dimensional convolutional neural networks are often applied to time-series data, such as sensory or accelerometer data. This allows us to apply them to raw EMG signals because of their temporal nature. The proposed architecture is composed of two convolution layers and an output layer. Each of the two convolutional layers consists of 64 filters and a kernel of size 8. The two convolutional layers employ the rectified linear activation function ReLU. The fully connected output layer size is equal to the number of gestures to classify. This layer uses a softmax activation function. The first layer is followed by a Pooling layer, performing a maximum sub-sampling over a window of size 17 and a stride equal to 9, as well as a Batch Normalization layer. Finally, a dropout layer follows each convolutional layer with a probability of 0.5. The architecture of the one-dimensional convolutional model is shown in Fig. 1.

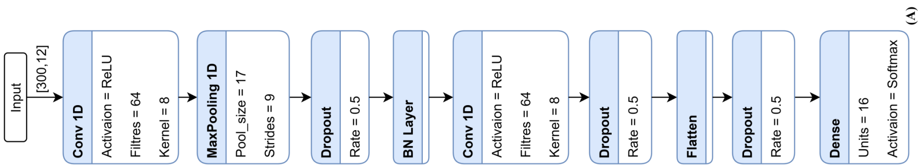

Fig. 1: Network architecture of the proposed 1D-CNN model.

4.2 CNN-2D Model

Two-dimensional Convolutional neural networks are generally used with image data input. However, we preferred in our case to keep the EMG data in its format without going through a transformation to an image as done by other works [2, 4, 18]. The nature of the signals is a matrix of two dimensions representing time-steps and EMG channels, respectively. We reshape these signals to a three dimensional data by setting the third dimension (the matrix depth) to 1.

The proposed architecture is illustrated in Fig. 2. It comprises 3 convolution layers, a fully connected layer and an output layer. The model input consists of a 300×12 (height × width) matrix, where the height is the window length (i.e. 300 samples, sampled at 2 kHz, which gives a window of 150 ms), and the width is equal to the number of electrodes. The first three hidden layers are convolutional, each composed of 32, 64 and 128 filters of size 20×3, 3×3 and 3×3, respectively. The next hidden layer is fully connected, consisting of 128 units. The network ends with a fully connected output layer connected to a softmax activation function (the number of output units represents the number of gestures to classify). Each hidden layer is connected to a rectified linear activation function ReLU. In addition to a Dropout layer on the third and fourth layers with a probability of 0.5. Finally, we added a Pooling layer to each of the three convolutional layers performing maximum subsampling on 10×1, 3×2 and 2×2 windows, respectively.

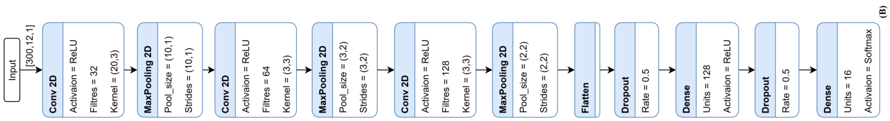

Fig. 2: Network architecture of the proposed 2D-CNN model.

5 Experimental Evaluation

In this subsection, we illustrate the various carried out tests and the experimental results for the implemented methods. First, we describe the evaluation data then

5.1 Data

In this study, we exploit a public dataset, namely NinaPro [3]. This multimodal dataset is used worldwide by scientific researchers. Most papers and systems use this database to simulate and compare their proposed works on hand gesture, robotics and medical neurocognitive [11, 16, 17]. NinaPro contains various hand and finger movements with multi-model signals such as accelerometer, EMG, force value, etc. NinaPro is composed of ten different datasets.

The EMG data used for evaluating our approach is collected from the second NinaPro repository. This set of datasets offer a benchmark database for evaluating non-invasive hand prosthetics. This part of the dataset contains myoelectric recordings collected using the Delsys Trigno EMG device, with a twelve wireless electrodes. The device sampling rate is 2 KHz. This database consists of

40 healthy subjects, where each one performs 49 different hand movements in addition to the rest hand posture. Each movement was repeated 6 times by each subject, and each repetition lasted 5 seconds followed by a resting posture lasting approximately 3 seconds. The database contains recordings of three different types of exercises, each type was recorded in a separate file [3]. These categories are as follows.

- From the 1st to the 17th movement: the basic movements of the fingers and wrist (flexion and extension),
- From the 18th to the 40th movement: grasping and functional movements,
- From the 41st to the 49th movement: the basic movements of the wrist (adduction/abduction, flexion/extension and pronation/supination).

We focused our study on the first category of movements. Table 1 enumerates the gestures we aim to recognize in our work.

Table 1: Hand gesture classes considered in our work.

Label	Gesture
1	Thumb up: flexing all fingers except thumb
2	V-sign: extension of index and middle finger while flexing others
3	German three: flexion of ring and little finger while extending others
4	Four: thumb opposing base of little finger
5	Open hand:abduction of the fingers
6	Close hand: all fingers flexed
7	Index pointer: extended index, with remaining fingers flexed
8	Joined fingers: adduction of extended fingers
9	Wrist supination (rotation axis through middle finger)
10	Wrist pronation (rotation axis through little finger)
11	Wrist flexion
12	Wrist extension
13	Wrist extension with closed hand
14	Wrist radial deviation
15	Wrist ulnar deviation

5.2 Results

Along with a good network design the training parameter tuning is central for obtaining good model. In our case, we at first inspired the initial values of training parameters from the previous works, and then we varied these values until obtaining a satisfying model. Our training parameters are provided in Table 2.

The performance of a machine learning algorithms is frequently assessed by measuring the accuracy of the classification, which is equal to the fraction of

Table 2: Training parameters.

Batch size	128
Optimizer	Adam
Loss	categorical cross-entropy
Learning rate	0.001
L2 Regularization parameter	0.01

correct classifications (true positives and true negatives) over the total number of classifications. Equation 1 expresses the overall accuracy.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}, \tag{1}$$

where TP, TN, FP and FN refer to true positive, true negative, false positive and false negative rates, respectively.

To evaluate our models for gesture recognition, we proceeded to subject-dependent evaluation strategy, where a separate model is trained and test using data from a unique person. Table 3 provides the performances of the two architecture, where we depict the average accuracy, the worst accuracy and the best accuracy along with training and test time.

Table 3: Performances of the proposed models on the NinaPro-DB2.

	Average acc.	Best acc.	Worst acc.	Train time	Average Test Time
CNN-1D	73.35% $\mp$ 5.93	85.73%	62.80%	00:59:50	0.181 ms
CNN-2D	73.12% $\mp$ 6.48	83.72%	56.93%	00:50:44	0.297 ms

As it can be noticed from Table 3 the one-dimensional CNN is the most efficient architecture, with an average accuracy of 75.35%, whereas the two-dimensional CNN model gives an overall precision of 73.12%. Moreover, 1D-CNN is faster on test which is more important although it has a higher training time.

For further analysis, we provide the global confusion matrices of each model in Fig. 3 and Fig. 4. It can be noticed that some gesture are easy to recognize (e.g. 9-Wrist supination and 13-Wrist extension with closed hand), while others (e.g. 0-Flexing all fingers except thumb and 14-Wrist radial deviation) provides low accuracies for both models. These last cases decrease the overall accuracies.

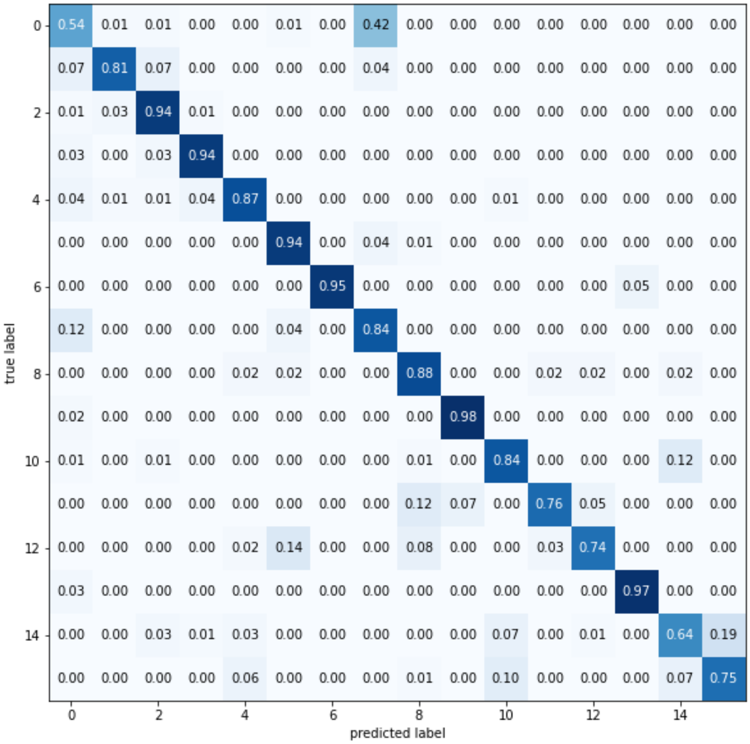

Fig. 3: Global confusion matrix of the 1D-CNN model.

6 Conclusion

In this paper, we designed a hand gesture recognition system based on EMG signals and deep convolutional neural networks. We proposed two network architectures one based on 1D convolutions and the other on 2D convolutions. We evaluated our model for the classification of fifteen hand gestures from the NinaPro DB2 database. The experiments show that the 1D-CNN model achieves better results both in terms of classification accuracy and classification time. For some subjects in the database, the classification accuracy exceeds 85% while classifying a hand gesture requires less than 0.2 ms, making the system suitable for embedding.

The experimental results show that some hand gestures are easier to recognize than others. Indeed, few gestures exhibit very low accuracy, which affects the

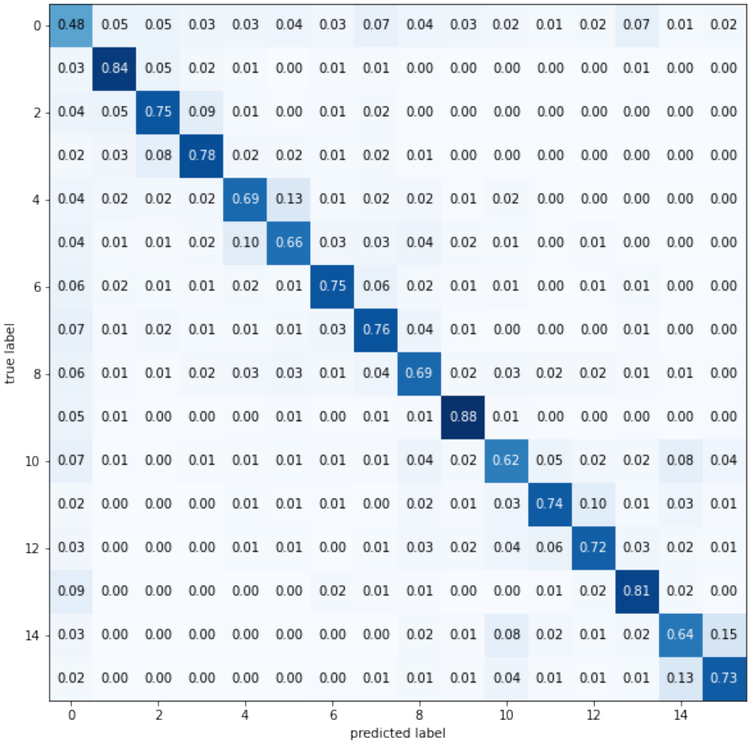

Fig. 4: Global confusion matrix of the 2D-CNN model.

overall performance. In the future work, we will tackle this issue. We also intend to test other network architectures and combine them with the proposed ones. Furthermore, our approach will be compared with the existing ones.

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