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Graph Neural Networks for HD EMG-based Movement Intention Recognition: An Initial Investigation

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***Abstract*—Recently, high-density (HD) EMG electrodes have been proposed for improving amputees' movement/grasping intention recognition, exploiting different machine learning techniques. HD EMG electrodes are composed of a large number of closely spaced channels that simultaneously acquire EMG signals from different parts of the muscle. Given the topological properties of these devices, it is important to fully exploit the spatio-temporal information provided by the electrodes to optimize recognition accuracy. In this work, we introduce the use of Graph Neural Networks (GNNs) to process HD EMG data for movement intention recognition of people with an amputation affecting the upper limbs and which use a robotic prosthesis. In this initial investigation of the approach, we conducted experiments using a real-world dataset consisting of EMG signals collected from 20 volunteers while performing 65 different gestures. We were able to detect 45 gestures with a classification error rate of less than 10%, and obtained an overall classification error rate of 8.75% with a standard deviation of 4.9. To the best of our knowledge, this is the first work in which GNNs are used for processing HD EMG data.**

***Index Terms*—HD-sEMG, GNN**

I. Introduction

In the last few years, there has been an increasing interest in exploiting sensors and artificial intelligence algorithms to support people with disabilities [1]–[3]. In particular, the electromyogram (EMG) signals acquired with surface electrodes from the residual muscles after amputation are widely used in conjunction with machine learning methods to decode the amputee's movement/grasping intention and control robotic prostheses [4], [5].

Of course, the availability of spatial and temporal information influences the performance of machine learning systems [6]. However, most of the works conducted until now have employed a low number of EMG electrodes, which provide little spatial information [7]. To increase the possibility of extracting spatial information, high-density EMG (HD-EMG) electrodes have been proposed [8], [9]. These employ a large two-dimensional (2D) array of closely spaced electrodes to acquire a large number of signals simultaneously from different parts of the muscle [10].

A few previous works have used HD-EMG electrodes to control robotic hands, including [11]. However, to our knowledge, no previous studies have used a graph neural network (GNN), in conjunction with HD-EMG signals, to identify the movement/grasping that the amputee intends to perform. GNNs are helpful in a context where a high number of temporally-correlated spatial information is available [12]. This kind of neural network is composed of several propagation modules, which propagate information between nodes so that the aggregated information can capture both feature-based and topological information [13].

In this paper, we propose the use of a GNN architecture for amputee movement recognition based on HD-EMG electrodes data. For building the graph, we considered 32 ms sliding windows, since shorter window sizes can be processed faster, leading to shorter controller delays and, consequently, better experience for the user.

We experimented our methods with a real-world dataset acquired from 20 participants wearing on the forearm two HD-EMG electrodes with 64 channels each to recognize 65 gestures. We obtained an average classification error rate of 8.75% with a standard deviation of 4.92, and 45 out of 65 gestures were detected with an error rate of less than 10%. These results, obtained with a baseline GNN implementation, are well aligned with the state of the art, and support the importance of further investigation of our approach.

The rest of the paper is structured as follows. Section II is divided in Subsection A, B, C and describes the material and methods used. Subsection A reports some information about the public HD-EMG dataset we used in our work. Subsection B explains how, based on the structure of the HD-EMG electrodes used, the graph was created. Subsection C give details on the EMG-GNN architecture. Section IV reports our experimental results. Finally, Section V concludes the paper and indicates future research directions.

II. Material and Methods

A. HD-EMG Dataset

In order to evaluate our method, we conducted extensive experiments with a recently released dataset [14]. Data were recorded at the forearm level from 20 able-bodied participants (14 men and 6 women) aged between 25 and 57 (mean age 35). Each participant performed five repetitions of 65 gestures, with a rest period of 5 seconds between each repetition.

The 65 gestures include:

- individual fingers flexions and extensions;
- thumb flexions, extensions, abductions and adductions;
- wrist flexions, extensions, pronations and supinations;
- some combinations of the above movements;
- some of the most common synergistic multi-joint hand movements.

For EMG data collection, the authors used two HD-sEMG electrodes, each consisting of 64 channels arranged in an 8×8 matrix with an inter-electrode spacing of 10 mm (ELSCH064NM3, OT Bioelettronica, Turin, Italy). The electrodes were placed approximately 3 cm from the elbow (elbow to closest electrode corner) and 2 cm from the ulna (edge of the ulna to edge of the electrode). The sensing device is shown in Fig. 1

The EMG signals were sampled at 2048 Hz. A hardware high-pass filter at 10 Hz and a low-pass filter at 900 Hz were used during recordings. To reduce the noise in the EMG signal consecutive channels were subtracted during the registration. Due to the orientation of the electrodes relative to the underlying muscles, the subtraction of the EMG signals was done along with the muscle i.e. ch1 signal was calculated as the difference between EMG signals at electrode contacts 2 and 1, ch2 as the difference between signals at contacts 3 and 2, and so on.

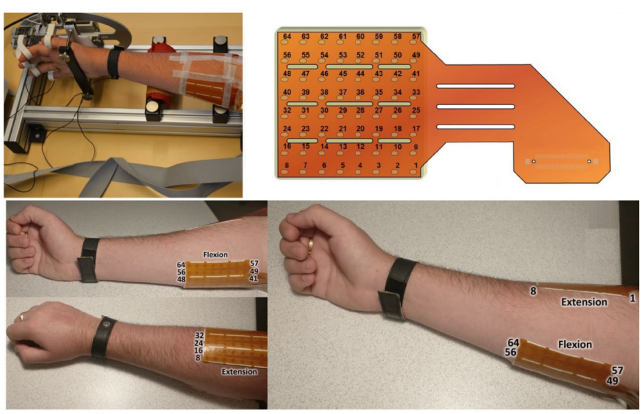

Fig. 1. HD-sEMG electrodes used in [14]

B. Graph-based modeling of HD-EMG data

In our graph-based model, each channel used to collect EMG data represents a node of the graph. We divided the signals from the different channels using non-overlapping sliding windows of 65 samples, corresponding to 32 ms of recording. Before division into sliding windows, the EMG signals were standardized, which implies scaling the distribution of values so that the mean of the observed values is 0 and the standard deviation is 1. Each node is associated with a feature vector corresponding to a sliding window containing a time sequence of 65 samples acquired from the respective channel.

Different strategies were proposed in related works to connect nodes by edges [15]. For the sake of this work, we decided to use a simple approach, where only nodes closer than a heuristic distance are connected. The resulting topology is shown in Fig. 2. As shown in the figure, in order to simultaneously consider the data acquired from the two electrodes, we added edges from the nodes of the first electrode's last row to the nearest nodes of the second electrode's first row.

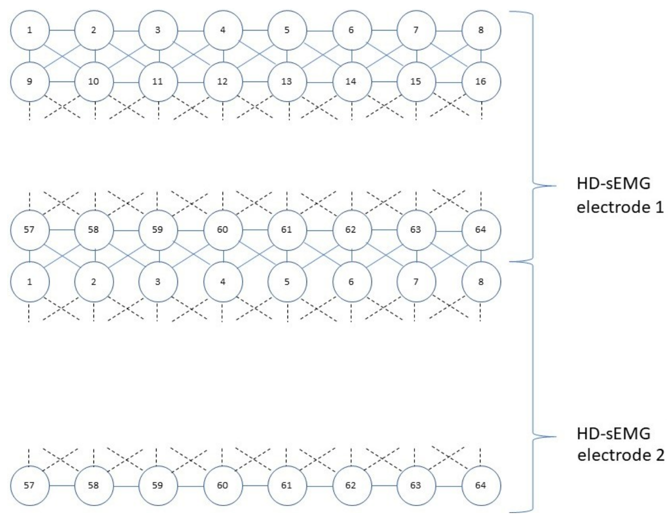

Fig. 2. The graph consists of 128 nodes and 884 edges. The structure of its channels is analogous to the organization of pixels in an image.

C. EMG-GNN Structure

The GNN structure is analogous to the one proposed in [15]. Its structure is shown in Fig. 3, and it consists of:

- graph convolutional layers and ReLU non-linearity applied to the signals mapped onto the graph structure to embed each node by performing multiple rounds of message passing;
- a READOUT function to learn the representation vector of the entire graph through the aggregation of the node representations from the final graph convolutional layer;
- a multi-layer perceptron (MLP) to classify the graph representation vector.

SAGEConv implements the GraphSAGE operator proposed in [16]. GraphSAGE is a general inductive framework that leverages node feature information to efficiently generate node embeddings for previously unseen data. This framework is designed for large graphs with a high number of nodes. GraphSAGE learns a function that generates embeddings by sampling and aggregating the local neighborhood features of a node, unlike most existing approaches that require all nodes

```
 EMG-GNN(
SAGEConv (65, 109)
ReLU Non-linear activation
SAGEConv (109, 109)
ReLU Non-linear activation
SAGEConv (109, 109)
ReLU Non-linear activation
SAGEConv (109, 109)
ReLU Non-linear activation
SAGEConv (109, 109)
ReLU Non-linear activation
SAGEConv (109, 109)
Global Mean Pooling
MLP (109, 109, 109, 109)
Dropout (p=0.5)
Linear (109, 66))
```

Fig. 3. Schema of the EMG-GNN structure

in the graph to be considered during embedding training.

We used the Adam Optimizer with a starting Learning Rate (LR) of 0.001. We also used ReduceLROnPlateau, which reduces the LR when a metric has stopped improving for a "patience" number of epochs. In our case, we monitor the Validation Loss, and if its value does not decrease for 10 epochs, the learning rate is reduced by 0.1.

We applied Cross-Entropy Loss and monitored the Validation Loss to decide when to stop training. The Early Stopping allows us to speed up learning and to avoid overfitting. If the Validation Loss value does not decrease for 30 epochs, model training is stopped; otherwise, the model is trained until the 100th epoch is executed.

We batched the graphs, setting the size to 32, before putting them into the GNN to ensure full GPU utilisation.

III. Experimental results

We decided to consider the different subjects' datasets separately during the trials. Therefore, before each trial we shuffled the graphs of a single subject's dataset, and then divided them into 60% training set, 20% validation set, and 20% test set.

Table I shows, for each gesture identified by a number in the first column, the standard deviation and the overall classification error rate (%) obtained by considering all the results achieved during the execution of the different trials. As mentioned above, only one subject's dataset was used during each trial. A usable system should achieve error rate levels less than 10% [17]. Then, we highlighted in red the gesture classification error rates higher than this percentage value, i.e., 20 gestures out of 65.

The most difficult gestures to recognize are:

- 10 Thumb: up
- 19 Little finger: bend + Thumb: left
- 24 Little finger: bend + Wrist: rotate clockwise
- 26 Ring finger: bend + Thumb: down
- 27 Ring finger: bend + Thumb: left
- 29 Ring finger: bend + Wrist: bend
- 30 Ring finger: bend + Wrist: stretch
- 31 Ring finger: bend + Wrist: rotate anti-clockwise
- 32 Ring finger: bend + Wrist: rotate clockwise
- 34 Middle finger: bend + Thumb: down
- 35 Middle finger: bend + Thumb: left
- 38 Middle finger: bend + Wrist: stretch
- 43 Index finger: bend + Thumb: right
- 52 Thumb: down + Wrist: rotate anti-clockwise
- 53 Thumb: down + Wrist: rotate clockwise
- 56 Wrist: stretch + Wrist: rotate anti-clockwise
- 57 Wrist: stretch + Wrist: rotate clockwise
- 59 All fingers: bend (without thumb)
- 64 3-digit pinch
- 65 3-digit pinch with Wrist: anti-clockwise rotation

The above list shows that the EMG-GNN has difficulty detecting mainly complex gestures with 2 or more degrees of freedom (DoF).

In the last row of Table I, we reported the standard deviation and the overall classification error rate (%) obtained by considering all the results achieved during the execution of the different trials, without taking into account the subdivision into gestures.

IV. Conclusion and future work

The use of machine learning and data from EMG sensors promise to enable novel important applications for people with disabilities. In this paper, we introduced a novel approach, using Graph Neural Networks for processing HD EMG data to support movement intention recognition of amputees. The use of Graph Neural Networks allows modeling complex topological relations of the electrodes, which are not captured by traditional machine learning algorithms or by other deep learning architectures. An initial investigation of our method, including experiments with a real-world dataset, show that the approach is promising.

Future work includes a deeper investigation of the spatio-temporal characteristics of HD EMG data to refine the graph structure. We are also considering to use explainable AI methods to investigate the internal functioning of the deep learning model to fine-tune the network structure for reducing the computational cost. Finally, we will experiment our methods with additional datasets, and perform an experimental comparison with state of the art techniques.

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TABLE I
STANDARD DEVIATION
AND OVERALL ERROR RATE (%).

Gesture	Standard deviation	Overall error rate (%)
1	4,14	4,32
2	7,13	6,16
3	6,11	6,58
4	5,84	6,16
5	4,43	4,89
6	6,79	6,74
7	5,88	6,84
8	5,49	4,26
9	7,78	8,63
10	6,66	11,68
11	6,87	9,42
12	7,1	9,11
13	3,09	3,37
14	5,38	4,37
15	3,39	4,47
16	4,54	4,63
17	7,11	6,63
18	7,49	8,95
19	8,89	10,21
20	5,35	8,16
21	6,12	6,89
22	6,6	8,74
23	6,66	7,74
24	7,19	10,26
25	6,64	7,42
26	9,52	14,42
27	10,16	14,58
28	5,06	8,47
29	8,89	12,26
30	9,15	12,84
31	10,1	12,37
32	8,98	12,21
33	3,78	6,74
34	5,32	10,32
35	6,94	11,21
36	5,67	8,74
37	7,88	8,63
38	10,18	12,37
39	5,77	7,95
40	7,52	8,84
41	4,94	6,84
42	7,2	9,58
43	8,65	11,16
44	7,03	8,05
45	7,3	9,42
46	6,96	8,84
47	8,39	9,26
48	8,46	8,26
49	5,9	6,58
50	5,27	7,79
51	5,9	7,26
52	9,67	11,58
53	10,05	11,53
54	8,06	8,53
55	7,12	8,47
56	11,27	12,89
57	6,84	10,21
58	4,31	4,74
59	11,9	11,42
60	6,13	8,32
61	6,46	8,63
62	5,46	7,05
63	5,57	7,74
64	10,83	14,58
65	8,93	11,63
Overall error rate (%)	**4,92**	**8,75**

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