Brain–Computer and Human–Machine Interfacing using Machine Learning Techniques

Ph.D. thesis

Melinda Rácz

János Szentágothai Neurosciences Division
Semmelweis University Doctoral School

Supervisor:	Gergely Márton, Ph.D
Official reviewers:	Péter Barthó, Ph.D
	Otília Menyhart, Ph.D

Head of the Complex Examination Committee:
Alán Alpár, D.Sc

Members of the Complex Examination Committee:
László Acsády, D.Sc
Márton Szemenyei, Ph.D

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1. Introduction

Brain–computer interfaces (BCIs) are a subtype of human–machine interfaces (HMIs)—systems that implement connection between an individual's brain and an actuator. The application of these solutions may improve the quality of life in patients with motor deficiencies, such as people with tetraplegia or locked-in syndrome resulting from e.g. amyotrophic lateral sclerosis or brainstem stroke.

There is a variety of signal modalities, paradigms and signal processing methods applied in the field. This thesis describes the implementation of a BCI and an HMI using machine learning (ML) methods. The BCI software classifies and predicts neuronal activities (spikes, action potentials—APs) recorded with intracortical multielectrode arrays and utilizes convolutional neural networks (CNNs). The HMI exploits myoelectric (EMG) artifacts in electroencephalography (EEG) signals and uses support vector machines (SVM) for driving a mobile robot.

2. Objectives

Objective 1: development of a CNN-based spike sorter

Spike sorting is a fundamental challenge of neuroscience. In recent years, ML methods, most importantly, CNNs emerged as possible solutions for the problem, surpassing hard-coded algorithms. Our objective is to implement a CNN-based spike sorting algorithm trained on real-life data encoding extracellular potentials, that uses samples from APs during their full time course.

Objective 2: development of a CNN-based spike predictor

In some applications, the system benefits from the shortest delay possible. Therefore, a sorter that is able to predict the class of a spike before the neuron actually fires, may have a utility in practice. Our objective is to determine the earliest point in time when spike sorting is already possible (assuming a 50 %

accuracy) based on samples from the local field potential preceding APs and/or the falling edge of the actual APs.

Objective 3: development of an EEG/EMG-based user interface for robot control utilizing a portable EEG headset

A practical demand imposed on HMIs is that they may require the least amount of training data for proper functioning. Among ML algorithms, SVMs are praised for their comparatively reduced need for training data. Our objective is to implement an SVM-based classifier that functions as an interface between a portable EEG headset and a mobile robot. The complete system is aimed at being applied for demonstrative purposes. Such demonstrations commonly involve subjects inexperienced at using BCIs that require training and/or special capabilities (such as motor imagery BCIs). The system to be implemented may exploit the presence of EMG artifacts in the EEG signal.

3. Methods

3.1. Spike sorting using CNNs

We used nine 45-minute-long recordings acquired from the primary somatosensory cortex of anesthetized Wistar rats, containing spontaneous brain activity. During data acquisition, a high-density complementary metal-oxide semiconductor MEA was applied with sites arranged into a 32 × 4 grid. Clusters and spike instances (timing information) were obtained from raw recordings using KiloSort and Phy.

Data of two different dimensionality were considered as samples. Two-dimensional data (frames) consisted of single instances taken at a specific time point from the vicinity of activity peaks. Three-dimensional or composite samples (timeslots) consisted of multiple instances (2D data) and contained information from the entirety of the action potentials. Three-layered CNNs (depicted in Figure 1) were applied for classifying and predicting activities, consisting of one convolutional and two dense layers. During training, we applied validation with early stopping as regularization.

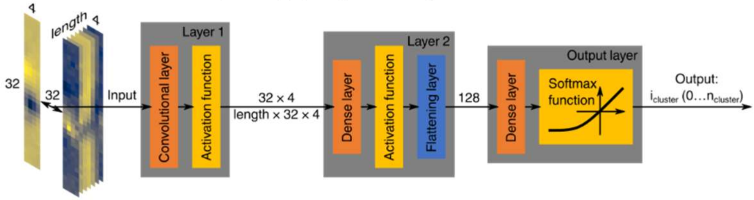

Figure 1. Structure of the CNN used for spike sorting and prediction. Source: own figure from (1);

We also addressed the problem of electrode drift, applying two separate partitioning of training, validation and test data. In the chronological database, training data consisted of the earliest samples in the recordings, followed by validation, and finally, test data. In the other experiment involving fully randomized data, samples were shuffled prior to applying the split. The detailed description of the methods outlined here can be found in (1).

3.1. Spike prediction using CNNs

For spike prediction, we used the same CNN architecture that was applied for sorting. The implementation differed only in utilizing samples shifted back in time, i.e. containing information related to the initiation of spikes.

Predictors were fit only to sequential data taken from Recording 4 of our database. The detailed description of the methods outlined here can be found in (1).

3.2. EEG/EMG data processing using SVM

We utilized 2-second-long EEG/EMG samples captured by portable EEG headset MindRove arc. Incoming signal was processed by a custom C# software that also prompted the users to perform facial gestures corresponding to the mobile robot turning right, steering forward and remaining idle. The operation of the software is demonstrated in Figure 2.

Samples were transformed into frequency domain using Fast Fourier Transform. Frequency components within the range (0, 80] Hz were kept for further processing. For discriminating the samples, C-support vector classification was applied. The detailed description of the methods outlined here can be found in (4).

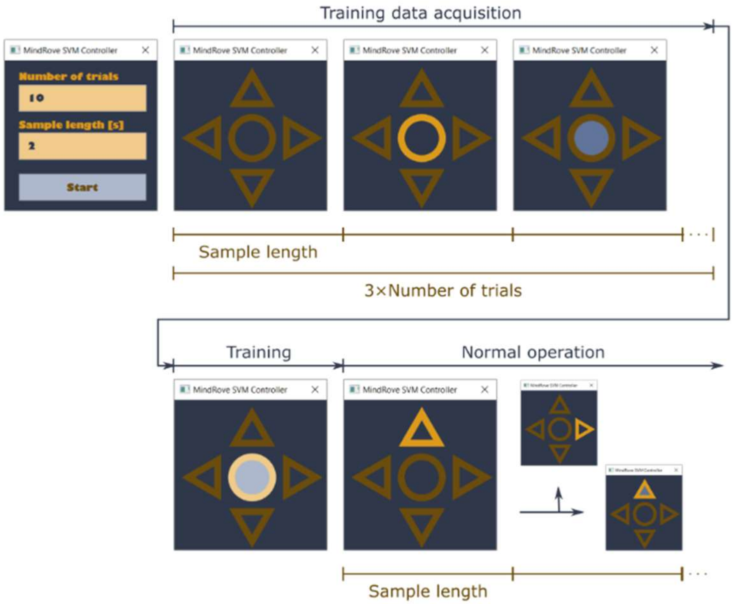

Figure 2. Data acquisition paradigm of the SVM classifier. Top row, from left to right: initialization window requesting the number of trials per class and the length of the data segments used in seconds. Then the software prompts the user to perform the gestures corresponding to the commands, namely, rest (no objects on the screen are highlighted), right turn (the outline of the central circle is highlighted in yellow), and forward movement (the fill of the circle is highlighted in blue). The actual order of the prompts is randomized. Bottom row, left to right: after sampling collection has ended, classifier training takes place (the outline and fill of the central circle is highlighted in light colours), then the software starts to classify incoming samples, indicating the active direction (with the outline of the corresponding arrow highlighted in yellow) and actual movement (with the fill of the arrow highlighted in blue). Source: own figure from (4).

4. Results

4.1 Spike sorting using CNNs

The performance of 2D and 3D classifiers were evaluated for all recordings. The accuracy of the sorters by recording is depicted in Figure 3. Averages by sorter type are shown in Figure 4.

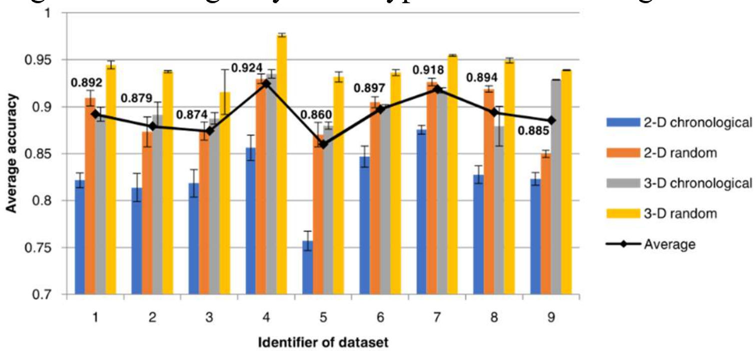

Figure 3. Effect of the data type (i.e. 2D and 3D) and the order of the training, validation and test samples (i.e. chronological and random) on the classification accuracy with respect to the recordings. Source: own figure from (1);

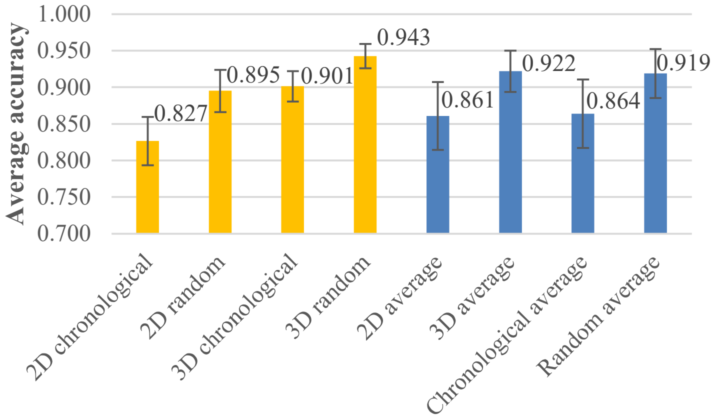

Figure 4. Yellow bars: average performance of the sorters across recordings. Blue bars: average performances across sorter type (2D or 3D) and training/validation/test database type (deterministic or random). Averages are shown with their respective standard deviations.

Performance of 3D sorters (92.2 %) was greater than that of their 2D counterparts (82.7 %) by a margin of 6.109 % on average. The performance of deterministic sorters (86.4 %) was inferior to the ones trained on fully randomized data (91.9 %) by a 5.493 % margin on average.

4.2 Spike prediction using CNNs

We encountered the best 2D predictor performance at an offset (i.e. number of sampling periods before KiloSort timestamps) of 1 (86.1 %). As the classifier shifts backwards along the falling edge of the spike, its accuracy monotonously decreases, reaching 50 % at an offset of 8 (50.3 %), that is, 0.35 milliseconds before spike peaks (given a sampling rate of 20 kHz and assuming the peak to be at an offset of 1). The characteristic curve showing the accuracy of the 2D predictor with respect to the offset is depicted on Figure 5.

Similarly, the accuracy of the 3D predictor reached 50 % when the last frame of the timeslots preceded KiloSort timestamps by 0.35 milliseconds (54.3 %, at a starting point of 28). The corresponding characteristic is shown in Figure 6.

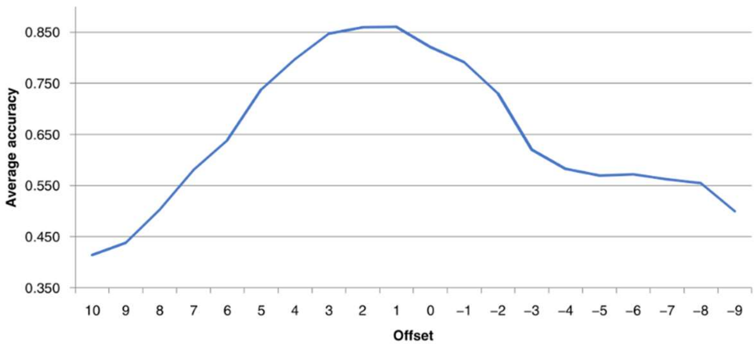

Figure 5. Accuracy of the 2D predictor with respect to the offset. Note that offset is positive when the frame in question precedes the mark, thus data points are in chronological order. Source: own figure from (1); © IOP Publishing. Reproduced with permission. All rights reserved.

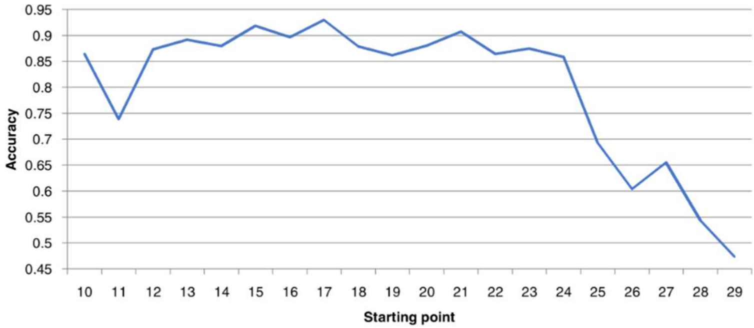

Figure 6. Accuracy of the 3D sorter/predictor with respect to the starting point. Source: own figure from (1); © IOP Publishing. Reproduced with permission. All rights reserved.

4.3. EEG/EMG data processing using SVM

Tests of the classifier were performed by one of the authors of (4) with the EEG headset placed above the parietal cortex. As control commands, eyebrow rising (switch direction) and chewing (steer forward) were applied. A run consisted of 20 two-seconds long training samples per class. As a result, we encountered an 86.67 % classification accuracy. A corresponding confusion matrix is shown in Figure 7.

Pattern following tests involving the robot model and the actual hardware in real world also were conducted with an average error of 12.39 %.

	0	**1**	**2**
0	13	7	0
1	0	19	1
2	0	0	20

Figure 7. Confusion matrix of the SVM classifier on data recorded by an experienced user. Classes 0, 1 and 2 correspond to rest, right turn and forward steering, respectively. Source: own figure from (4).

5. Conclusions

This work described the implementation of a SUA-based BCI software and an HMI for mobile robot control. The former solution applies a CNN-based classifier with spike sorting and activity prediction capabilities while the latter utilizes EMG artifacts corresponding to facial gestures and employs an SVM classifier.

We have proven that these two systems are capable, exhibiting performance that can compete with prior and recent results in the literature. Our 2D and 3D sorters yielded 86.1 and 92.2 % average accuracy, respectively. The robot controller exhibited 86.67 % accuracy during preliminary investigations and the complete system showed 12.39 % error in a pattern following test.

6. Bibliography of the candidate's publications

Publications related to the thesis:

1. Rácz M, Liber C, Németh E, Fiáth R, Rokai J, Harmati I, et al. Spike detection and sorting with deep learning. J Neural Eng. 2020;17(1).
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4. Rácz M, Noboa E, Détár B, Nemes Á, Galambos P, Szűcs L, et al. PlatypOUs—A Mobile Robot Platform and Demonstration Tool Supporting STEM Education. Sensors. 2022;22(6).

Publications not related to the thesis:

5. Matusz VI, Racz M, Rokai J, Jorgosz NE, Molnar T, Maraki D, et al. Head-mounted, wireless eyetracker for real-Time gaze prediction utilizing machine-learning. In: Proceedings of the 2020 IEEE International Conference on Human-Machine Systems, ICHMS 2020. 2020.
6. Horváth D, Négyesi J, Rácz M, Győri T, Matics Z, Puskin A, et al. Feasibility of a novel neurofeedback system: a parallel randomized single-blinded pilot study. Sci Rep. 2023;13(1):32.

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