

Automatic Methods for Motor Intention Recognition from Spike Rates

Jugoslava Acimovic[†], Alexandra Battaglia-Mayer[‡], Roberto Caminiti[‡], Martin Hasler[†]

[†]Laboratory of Nonlinear Systems (LANOS),
Ecole Polytechnique Fédérale de Lausanne (EPFL), Lausanne CH-1015, Switzerland.

[‡]Dipartimento di Fisiologia umana e Farmacologia
Università di Roma "La Sapienza", 00185 Rome, Italy.

Email: jugoslava.acimovic@epfl.ch.

Abstract—In this paper we present a method for automatic detection of motor intention from in vivo neuronal recordings in monkeys. The analysis relies on a data base of spike trains collected in a series of experiments aiming to study the hand-eye coordination mechanisms in primates. The neural activity is recorded using a multi-electrode system that can monitor up to fourteen neurons at time. In this work we analyze the possibility to “read” the motor intention from the set of simultaneously recorded spike trains, by combining the information from all the available recordings. We show that the information of interest can be successfully extracted from the data, under some constraints. First, we show the analysis of spike trains, segmented according to the behavioral epochs defined by the experiments protocol, and give the discussion of the proposed method performance in extracting the information of interest, i.e. the presence/absence of motor intention. Also, we consider a less ‘controlled’ analysis of entire spike trains, without segmenting, where the relevant information is more mixed with the side-effect processes, and accordingly, more difficult to recognize.

1. Introduction

This work aims to examine the processes in the brain of primates, related to motor activities, particularly hand control and hand-eyes coordination. We examine the question whether the information we interpret as ‘motor intention’ can be attributed to the spike trains recorded from the parietal cortex of a monkey performing a series of behavioral tasks. The positive answer presented in this paper shows that the underlying assumptions are correct, or at least not in contradiction with the experimental data. Among the different uses one can imagine for this information, is the control of motor prosthesis for patients with an impaired motor control system, [3], [4]. Actually, many functions typical of neural control of movement can be taken over by automatic control methods whose input signals are sensory stimuli, such as visual information about target location in space. However, the intention to move does not rely only on the input. It uses also, internally generated information in the brain and, therefore, must be extracted in some way from neural activity.

We present a machine learning based analysis of spike train recordings, aiming to classify neural activity according to presence/absence of intention for making a movement. The conducted analysis relies upon the hypothesis that we could ‘read’ motor intention from the set of simultaneously recorded spike trains, by combining information from all of the available recordings. Data analysis was kept at the level of spike rates, and the obtained results prove it to be a sufficient approximation for this particular classification problem. The first problem of interest was to distinguish between behavioral tasks, depending on whether or not neural activity in a selected set of task-epochs encodes intention for movement. In the second problem, we have explored the possibility of detecting the time of emergence of motor intention from spike trains where no a priori assumptions had been made concerning temporal epochs potentially encoding the animal’s intention to move. The results obtained for the first problem show much better performance, as a result of the introduction of a priori knowledge about relevant epochs to be used in the analysis. The second algorithm shows poorer performance, still the classification error is kept on 30% of wrongly classified data points, on average.

2. Data Base

2.1. Experiments Description

The presented work relies on a data base of spike trains, obtained in a series of extracellular neuronal recordings, designed for studying mechanisms of hand-eyes coordination in primates. The recordings are done on the 7a area of the parietal lobe, left hemisphere, for two rhesus monkeys. The detailed description of the experiments, and the analysis conducted so far are given in [1], [2].

The monkey is placed in front of a touch-sensitive screen, waiting for a target to appear in one of eight positions. At the same time, an instruction which task should be performed is indicated.

- *Reach task (R)*: The monkey is required to touch the target appearing on the screen. Naturally, it will first look, and then reach for it.

- *Reach fixation task (RF)*: Similarly, when the target appears on the screen, the monkey should touch it, but keep-

ing the eyes fixed to the center of the screen during the whole experiment.

- *Memory tasks*: The goal of the memory tasks is to exclude the influence of visual signals processing, by introducing the target memorization step. In the three tasks, the monkey is required to memorize the target position without moving. After the target disappears from the screen, the movement toward the memorized position occurs. It is either eye-only movement (*Memory eye task (ME)*), or hand-only movement with the eyes fixed to the center (*Memory reach fixation task (MRF)*), or both, hand and eyes movement (*Memory reach (MR)*).

- *No-go (NGO)*: In this task, no action should occur. The neuronal activity is recorded in the absence of the action of interest.

The 7-electrode system for recording neuronal activity is used. It can monitor up to fourteen neurons simultaneously.

2.2. Data Base Organization

Figure 1 illustrates the organization of the data base. The full described set of experiments is repeated for two lab monkeys, for several electrode positions. The collection of recordings from the same site will be called *file*. The two data bases, obtained from two monkeys, contain 45 and 57 files, respectively. One file contains recordings obtained from all six tasks, repeated for each of eight possible target positions. In addition, for each task and target choice, the experiment is repeated four times. Therefore, each file contains at most $6 \times 8 \times 4$ recordings. One recording results in a set of up to fourteen spike trains. In addition, the eye and the hand positions are also monitored, for control of the experiments, but these data are not relevant for the presented analysis.

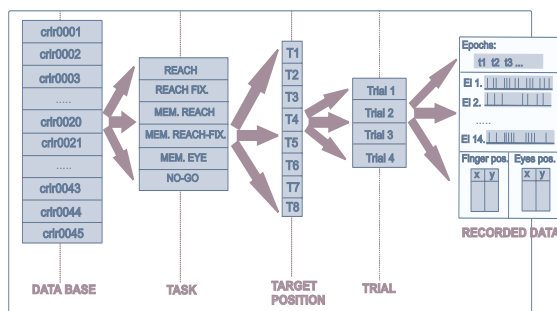


Figure 1: The schematic data base organization.

3. Methods

In the presented work, recorded data are analyzed on the level of spike rates. Rates are obtained as a spike count in a certain time interval, divided with the duration of that interval. In the sections describing data analysis methods, we give the detailed receipts for the rates calculations.

The choice of working with spike rates, rather than spike times, is a question that requires a further discussion. The usual arguments against rate codes holds here also [5]. In order to represent data using spike rates, it is necessary to adopt a certain time interval for rates calculation. Therefore, such representation includes a delay, that is inconsistent with the execution of rapid actions, e.g. eye movements [6]. While it is clear that the rate codes cannot mimic all the functionality of real neuronal systems, we will show that, even such coarse representation of the neuronal activity, provides enough information for the successful extraction of motor intention.

The problem of interest is to distinguish between spike train recordings which encode the intention for making a movement, from those corresponding to no movement planned. We consider the term 'movement' in the most general sense - any movement anticipated in the experiment, involving eyes or hand. The underlying hypothesis is that the presence of intention for moving corresponds to the modulation of the firing rate in the recorded neurons. This is a plausible assumption for the particular recorded set of neurons. The monitored brain region is believed to be responsible for hand-eyes coordination in primates. Therefore, it is realistic to expect that its neurons become more active, in order to exchange more information, during a movement planning and execution. We refer to these phenomena as 'motor intention' in this work.

We present the two methods for data classification with respect to the proposed criteria. The adopted machine learning algorithm is the same in both cases, but the data preprocessing step differs. The applied classifier is the standard multi layer perceptron network, with the gradient descent backpropagation training. One such classifier is created for each of the files in the data base. The number of network inputs corresponds to the number of neurons recorded simultaneously, which varies from file to file, but cannot be greater than fourteen. The system has a binary output, giving the answer whether the input data contains motor intention or not. The number of perceptrons in the hidden layer is determined by cross-validation.

3.1. Classification Based on Selected Data Segments.

The first classification problem of interest is: sorting the experimental tasks with respect to presence of motor intention (and as a consequence, presence of a movement) in at least one epoch anticipated by the tasks protocol. Since we do not consider the differences between eyes and hand movements, five tasks (R, RF, and three memory tasks) are labeled as *Motor intention present*, while NGO task corresponds to *No motor intention* class. In order to deal with the resulting unbalanced problem, data examples from the smaller class are repeated after the selection of learning, validation and test set.

The algorithm is presented on Figure 2. A spike rate is calculated for each spike train, using just a relevant part of the recording. We consider only the intervals where the

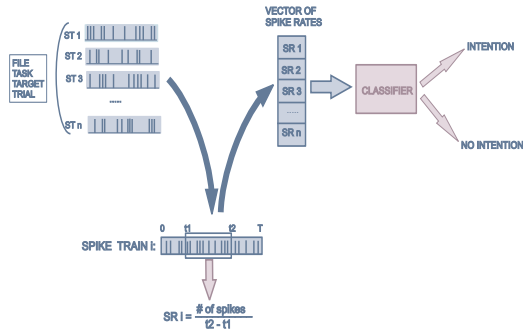


Figure 2: First algorithm. 14 spike trains are converted into a vector of spike rates. The a priori selected, relevant, data segment is used.

actual movement occurs for R,RF, and memory tasks, and the corresponding interval for NGO. This way, each set of simultaneously recorded data is converted into a vector of spike rates, with the dimension up to 14. This procedure results in the set of 192 data examples which is, then, divided into learning, validation and test set, in order to construct the classifier.

3.2. Classification on Entire Recordings

The second algorithm, presented on Figure 3, aims at detecting the appearance of motor intention in time. The complete recordings were considered rather than just a set of selected epochs. The number of data examples, as well as the temporal resolution, are defined by an adopted time window. The window is moving along the spike trains in discrete time steps, with the predefined time shift. For each distinct window position, spike rates are calculated in the standard way, as the number of spikes within the window divided by the window size. The considered window size is 1000msec, and the time shift is set at 200msec. The average length of the recordings is, approximately, 10 sec; therefore we consider around 10% of the available data in each step, with 4/5 overlapping between two succeeding steps. The resulting data are spike rates, again, but now, one set of spike trains gives several rate vectors. All data obtained this way are used for constructing the learning, validation and test set.

For the data labeling, we make the hypothesis about presence/absence of motor intention in certain phases of the experiment. Spike rate vectors are labeled in accordance with the corresponding spike trains segments. In some cases, the window position do not allow clear labeling (i.e. it can overlap some motor intention and some no motor intention segments). Such data are excluded from the training phase. In the test phase, we use the reliably labeled data for evaluating the classifier performance on average, but also the complete data set (including the non-labeled data) to obtain an additional information about the phenomenon of interest.

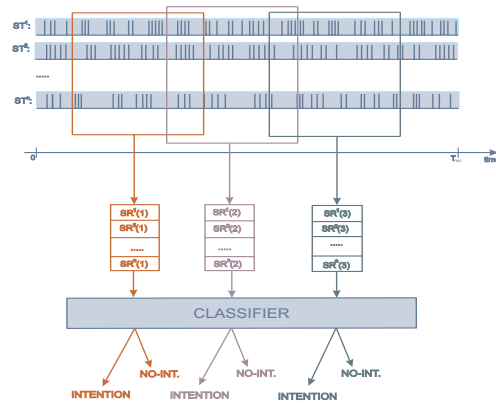


Figure 3: Second algorithm. The complete recording considered - spike rates for the three window positions presented.

4. Results

Figure 4 shows the average performance of the described algorithms for the two data bases. The upper two figures give results for the first method, and the lower two for the second one. The two data bases are represented column-wise. Each bar on the figure gives the average classification error for one file, in percents of the total number of data examples. The presented errors are calculated for the test set. For each file, on the x-axis is noted the number of recorded neurons for that file.

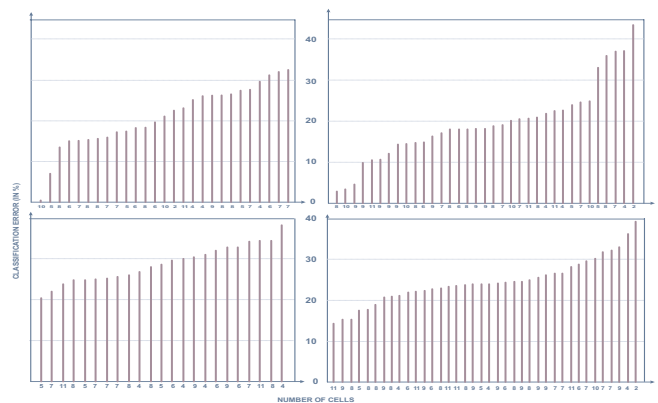


Figure 4: Average classification error. First method - upper figures, second - lower ones. Each bar is the error for one file. x axis - number of recorded neurons in the file; y axis - the classification error (in %).

Comparison of the obtained results show better performance of the first algorithm. Majority of the files give the classification error below 30%, and often it is less than 20%, particularly for the second data base (figures on the right). For the second algorithm, we obtain an increase of the error, since it is rarely below 20%, but remains less than

30% for most of the files. This is the expected results, since the second method attempts to solve more complex classification problem. In the first method, the part of the classification is done 'in advance', in the preprocessing phase, by choosing the right data segments for spike rates calculation. The obtained classification error, shows that it is possible to extract motor intention from the presented data, using a conventional machine learning algorithm. For the second considered problem, the applied data analysis allows influence of many side-effect processes, that mask the information to be extracted. Still, the presented figures show that the classification can be done with a certain precision.

Figure 5 shows some examples of 'on-line' classification using the second algorithm. Here, the performance on the selected set of examples is examined. Each considered set of spike trains is segmented and converted into spike rate vectors in the usual way. The classifier output is the probability of finding motor intention in the spike rates vector given as the input, i.e. in the corresponding data segment.



Figure 5: 'On-line' classification using the second method. Some examples. x axis - recording time, y axis - probability of finding motor intention in the data.

The shaded area on the figures corresponds to the epochs where the motor intention is expected. The curve gives the classifier outputs. For some of the examples, the maximal probability of motor intention falls around the shaded area (subfigures 1,3,4,5,6,7), but we can find some examples where it does not hold (2,8,10). As expected, NGO data show much smaller classification probability. Also, very often the motor intention appears before (or even after) the shaded interval. This should not be considered as error, since those examples correspond to data that cannot

be reliably labeled a priori, due to the corresponding data segments position. Also, it can happen that the motor intention appears before the expected time, while monkey is still waiting for the instructions.

The influence of the window size, as well as the a priori choice of motor intention segments will be examined in the future work.

5. Conclusion

This paper presents two methods for automatic detection of motor intention from multi-electrode and multi-tasks recordings of neuronal activity in monkeys. The first approach analyzes the a priori chosen time intervals of the recordings, believed to contain the motor intention. The obtained results show that motor intention can be recognized using the standard machine learning methods. The second method, aims to detect the recording intervals when motor intention is present. In this case, the relevant data is masked by other processes present during the movement, and consequently, the classification problem becomes more complex. The resulting performance is deteriorated, but the classification is still possible, according to the obtained results.

Acknowledgments

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