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Direct and inverse solution for a stimulus adaptation problem using SVR

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Abstract. Adapting stimuli to stabilize neural responses is an important problem in the context of cortical prostheses. This paper describes two approaches for stimulus adaptation using support vector regression (SVR). One approach involves the solution of an inverse problem and it is shown that for linear SVR an analytical solution exists. The proposed algorithms are evaluated in conjunction with different preprocessing methods an three datasets recorded from the barrel cortex of anasthesized rats.

1 Introduction

Cortical prostheses is a promising technology to aid people with defects in the sensory system, but there are still a lot of problems to be solved by biomedical engineers before their widespread application. For the visual system different prosthetic interfaces are conceivable [1] although the only help for severely impaired patients is the direct stimulation of neurons in visual cortex. This stimulation, which can be either intracortical [2] or epicortical [3], leads to the perception of phosphenes of various sizes and at different locations in depth. Since the mapping of activity from the retina to the cortical areas is retinotopic (preserves space relations), stimulation at different spatial locations in visual cortex can be used to construct simple shapes, e.g. letters, from single phosphenes [4]. Unfortunately neural responses evoked by cortical stimulation may depend on functional brain states, as for example the background activity of the brain is assumed to change the signal transmission properties of neurons [5, 6]. To ameliorate these effects one possible solution is the adaptation of stimulus intensities. As testing the viability of this approach in human subjects is not possible recordings made during micro-stimulation in the barrel cortex of anasthesized rats [7] are used in this paper.

The remaining part of this paper is structured as follows. In section 2 a brief description of the experimental setup for recording of data is described. Section 3 gives a formal description of the adaptation problem and the approaches proposed for its solution. Results for these approaches are presented in section 4 and summarized in section 5

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2 Experimental setup

In each experiment nerve signals are recorded from rat barrel cortex with 20KHz sampling rate while stimulation with a biphasic rectangular pulse occurs every 2s with different intensities in the range of $0.8, 1.6, \ldots, 4.8$nC. The spontaneous neural activity and stimulus response for one trial is shown in figure 1 on the right where the time-scale is centered on stimulation onset and the inset shows the neural response in detail. All results given in section 4 are based on three datasets recorded at cortical depths of $1218, 950$ and 700μm.

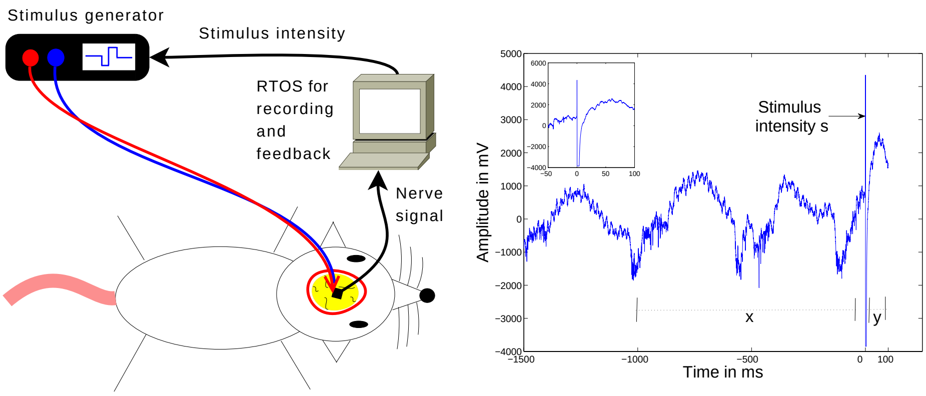

Fig. 1: Overview of the experimental setup for stimulation and recording from rat barrel cortex (left). Spontaneous neural activity and response for stimulation with 2.4nC (right).

3 Algorithms for stimulus adaptation

The direct solution for the adaptation of stimulus intensities is based on estimating a function $f(x, y) \mapsto s$, where x, y are the pre- and post-stimulus activities of the neurons (figure 1, right) and s is the stimulation intensity. When f is known the stimulus intensity for eliciting a certain target response y^* can be determined by evaluating $f(x, y^*)$.

Although this is the most straightforward solution for the problem it is also possible to first model the relationship between neural activity x and the stimulus response y by estimating a set of functions $\mathbf{f}(x, s) \mapsto y$ and then finding function $g(x, y^*) \mapsto s$ for a desired target response y^*. In this case the function g is the solution of an inverse problem. Since in both approaches support vector regression [8] is used for estimating f and $\mathbf{f}$ respectively, the next section explains how to find function g.

3.1 Solving the inverse problem

Denote by $f_j(x') = \langle w'_j, x'\rangle + b_j$ the j-th function in the set of functions $\mathbf{f}(x, s) \mapsto y$, where the vector $x' = (s, x)$ is assumed to have the stimulus intensity as its first component and similar $w'_j = (w^s_j w_j)$. The solution to the inverse problem is now given by minimizing the loss between $\mathbf{f}(x')$ and a target response y^* in dependece of s. In case of l2-norm loss this can be stated as the following optimization problem

$$\min_s \frac{1}{2}\|\mathbf{f}(x') - y^*\|^2 \;\; s.t. \; l \leq s \leq u,$$

where $l, u \in \mathbb{R}$ are upper and lower bounds for the stimulus intensities. Since the constraint can be enforced by a simple projection to the interval $[l, u]$ the unconstrained optimization problem can be directly solved for s.[1] Let

$$h(s) = \frac{1}{2}\|\mathbf{f}(x') - y^*\|^2 = \frac{1}{2}\sum_j (sw^s_j + \langle w_j, x\rangle + b_j - y^*_j)^2.$$

Computing the derivative and setting it to zero yields:

$$h(s)' = \sum_j (sw^s_j + \langle w_j, x\rangle + b_j - y^*_j)w^s_j \stackrel{!}{=} 0$$
$$\Leftrightarrow s \stackrel{\text{(a)}}{=} \frac{\sum_j (y^*_j - \langle w_j, x\rangle - b_j)w^s_j}{\sum_j (w^s_j)^2}.$$

Since $h(s)'' = \sum_j (w^s_j)^2 \geq 0$ the value of s is a local minimum of $h(s)$ and the desired function $g(x, y^*_j) \mapsto s$ is given by evaluating (a).

3.2 Preprocessing

After linear scaling to the interval $[-1, +1]$ the neural raw data is either bandpass filtered between 1-200Hz (Butterworth order 2) to extract the local field potential (LFP) or it is bandpass filtered between 300-6000Hz (Butterworth order 3) followed by clipping of extreme values, rectification and low-pass filtering at 100Hz to extract the multi-unit activity (MUA) [9]. To reduce dimensionality LFP and MUA are down-sampled to 500Hz and then either binned [2] (100ms, 10ms bins) or projected onto the 50 most dominant principal components [10]. In addition the LFP is subjected either to a phase analysis using the Hilbert-Transform [11] or a spectral analysis with power estimated in the α- (1-13Hz), β- (13-30Hz), γ- (60Hz) and γ_h-band (60-100Hz) [9]. Figure 2 summarizes the different methods and introduces the abbreviations used in section 4. These preprocessing steps are applied to 1.5s pre- and 100ms post-stimulus data for the direct approach and to 1.5s prestimulus data for the inverse approach. In case of the inverse approach 20ms of post-stimulus data are low-pass filtered at

[1] This is possible since the objective function is convex with respect to s.

[2] In this context binning means computing the average across a certain time window.

40Hz and then projected to a 10-dimensional principal component subspace to represent the neural responses. All target values and the stimulus intensities are scaled to the interval [0, 1] to speed up the model selection which is described in the next section.

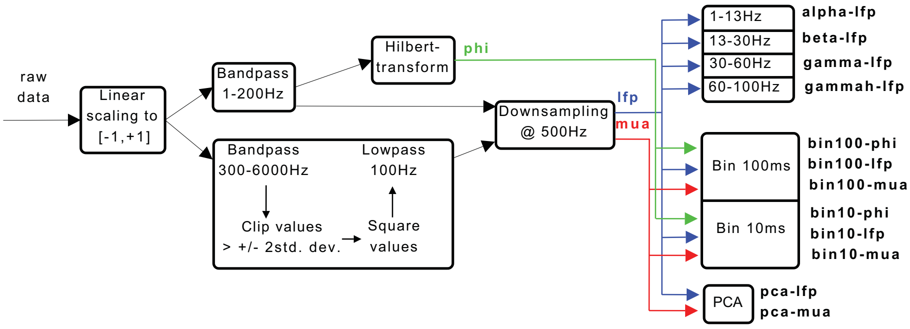

Fig. 2: Summary of different preprocessing steps. Note that combined features are denoted by "+" in the following, e.g. **pca-lfp+mua** means PCA coefficients for LFP and MUA data.

3.3 Model selection

Regularization parameter C and loss function parameter ε of linear SVR are selected by minimizing the minimum span bound [12, 13]. Since very large values of ε van lead to an empty set of support vectors the algorithms described in [14] is extended to include a simple backtracking scheme to avoid such regions in parameter space.

4 Results

The prediction performance of the direct and indirect solution is evaluated on the three datasets described in section 2. For each dataset 10 random partitions into 50% train and 50% test data are used to get a performance estimate. Detailed results of both approaches in conjunction with different preprocessing steps are shown in figure 3 for the first dataset. Table 1 summarizes the best results on the test set for all three datasets.

For the examined datasets spectral analysis and phase analysis of the LFP leads to less informative features in comparison with features extracted from the LFP and MUA directly. With respect to the two approaches MUA features work better for the inverse solution and LFP features for the direct solution.

Performance results indicate that both approaches are suitable for predicting stimulation intensities when they are used with certain preprocessing steps. For the direct approach results are slightly better in terms of RMSE for the second and third dataset, although it is more sensitive with respect to the preprocessing method. Another problem with the direct approach is its tendency to overfit the training data (e.g. figure 3, lfp) which is less severe when using the inverse approach. This is not surprising since the inverse solution uses a set of linear functions for predicting stimulus intensities while the prediction of the direct solution is based on only one function.

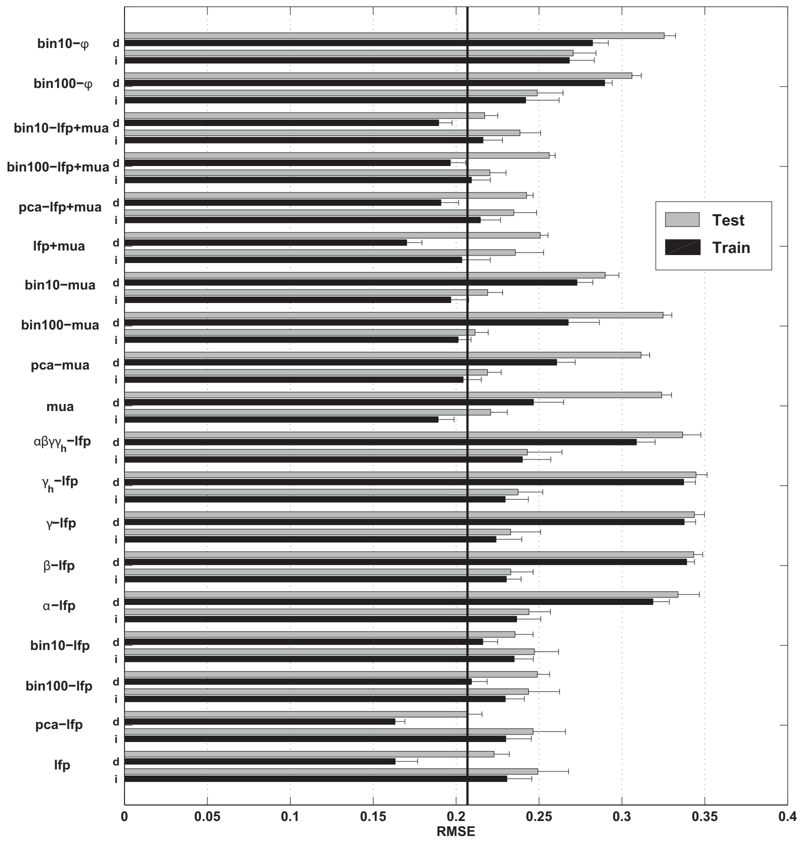

Fig. 3: Average performance of direct (d) and inverse (i) solution for predicting stimulus intensities on 10 random train/test partitions of the first dataset. Error-bars indicate standard deviations and the vertical line the best average performance on the test dataset.

5 Conclusion

This paper introduced two solutions for a stimulus adaptation problem based on linear SVR. Although both solutions yield similar performance results on three different datasets the proposed approach based on the inverse solution seems to be more robust with respect to over-fitting and selectio of a particular

Direct			Inverse		
Prep.	RMSE	ρ^2	Prep.	RMSE	ρ^2
pca-lfp	0.21 ± 0.01	0.64 ± 0.03	bin100-mua	0.21 ± 0.01	0.67 ± 0.02
pca-lfp	0.15 ± 0.01	0.82 ± 0.01	bin10-mua	0.16 ± 0.01	0.84 ± 0.01
bin10-lfp+mua	0.17 ± 0.01	0.77 ± 0.02	bin100-mua	0.19 ± 0.01	0.74 ± 0.01

Table 1: Best prediction results of direct and inverse solution with corresponding preprocessing method for dataset 1-3 (top to bottom). RMSE = root mean squared error. ρ^2 = squared Pearson correlation coefficient.

preprocessing method. In future work these solutions will be tested not only on offline data but also in an online feedback system, with the goal of stabilizing neural responses by adapting stimulation intensities.

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