

## On-line adaptation of neuro-prostheses with neuronal evaluation signals

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**Abstract.** Experiments have demonstrated that prosthetic devices can in principle be controlled by brain signals. However, in stable long-term applications neuroprostheses may suffer substantially from non-stationarities of the recorded signals. Such changes currently require supervised re-learning procedures which must be conducted under laboratory conditions, hampering the envisioned everyday use of such devices. As an alternative we here propose an on-line adaptation scheme that exploits a secondary signal source from brain regions reflecting the user's affective evaluation of the neuro-prosthetic's performance. Using realistic assumptions about recordable signals and their noise levels, our simulations show that prosthetic devices can be adapted successfully during normal, everyday usage.

### 1 Introduction

It is now well established that neuronal activity in motor cortex contains useful information about the desired movement of limbs [1, 2]. In many experiments neurophysiological data (action potentials, LFP's, EEG's) together with the difference between the desired and actual movement of the neural prosthetic device have successfully been used to adapt estimators that can compute control signals for prostheses [3].

Voluntary use of neuro-prostheses in normal life outside a laboratory, however, will naturally entail ongoing changes in the characteristics of the observed neurons and in the physical properties of the prosthesis. Therefore, with time the situation will differ more and more from the one to which the estimator initially was trained and render the prosthesis useless after some time.

A standard solution for this problem is to re-train the prosthesis by requiring the subject to perform a well-defined task in regular intervals [4]. Only if the desired movement is known, the performance can be accessed by an external observer, and subsequently be used to adapt the mapping between brain activity and the control signal for executing the intended movement of the limb. The drawbacks of this scheme are obvious: Everyday use of the prosthesis will be interrupted by retraining sessions. Between training epochs, the performance of the prosthetic device will still decay, and it is particularly unlikely that it

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can recover from abrupt changes of the recordings induced e.g. by shifts of the electrodes.

For voluntary movements, the error between desired and actual movement is per definition unknown to an external observer. Here we propose to record additional signals available in the brain which provide the missing information. This idea has several potential advantages for a disabled subject: it can eliminate the need for doing tedious training tasks in a clinical environment, and both adaptation and even initial calibration can be done during the everyday use of the prosthesis.

We demonstrate the feasibility of our approach by a numerical simulation using realistic assumptions about the origin and quality of neural signals. We demonstrate that the quality of signals from current recording technology is sufficient for a successful application of the adaptation and decoding algorithms.

## 2 Models of prosthesis and neural recording

Our model (Fig. 1) comprises an 'internal', and an 'external' part. The internal part consists of two neuronal populations from which an intended movement signal and an error signal are recorded, respectively. The external part of the model is the controlling system consisting of estimation and adaptation algorithms, and a robotic arm. The estimation algorithms decode both, the intended movement signal and the error signal. The estimated intended movement is used to control the robotic arm. In parallel, the error signal, which is assumed to be correlated to the mismatch between the intended and perceived movement, is used to adapt the decoding algorithm of the intended movement signal.

The intended movement in two dimensions can be described by a velocity vector  $\mathbf{v} = \{v \cos(\varphi), v \sin(\varphi)\}$  with direction  $\varphi$  and absolute value  $v$  ranging from 0 to  $v_{\max}$ . Recording in our simulation is done on  $N_v = 64$  neurons with cosine-shaped tuning curves for the direction and linear speed modulation. The mean firing rate  $f_i$  of neuron  $i$  is  $f_i(\mathbf{v}) = f_i^{\text{off}} + f_i^{\text{mod}}/2 (1 + v/v_{\max} \cos(\varphi - \varphi_i))$ .  $f_i^{\text{off}}$  denotes the baseline,  $f_i^{\text{mod}}$  the maximum modulation of the firing rate, and  $\varphi_i$  indicates the preferred direction of the neuron.

In order to simulate a situation like in real experimental recordings (a sort of worst-case scenario), we allow 25% of the neurons to be not tuned at all (creating uncorrelated noise), and we also allow for a large fraction (50%) of silent neurons (firing rates below 3 Hz). The remaining 25% of the neurons are chosen such that  $f_i^{\text{mod}} + f_i^{\text{off}}$  does not exceed 50 Hz. Direction tuning preference  $\varphi_i$  is assigned randomly, which yields a very inhomogeneous coverage of the movement angles between 0 and  $2\pi$ . Without loss of generality, we set  $v_{\max} = 1$  and  $T = 1$  s in the simulations.

The firing of the neurons is described by a Poissonian process. For each interval  $T$ , a vector of spike counts  $\mathbf{k} = \{k_1, \dots, k_{N_v}\}$  is drawn from the Poissonian distribution with the tuning functions  $f_i(\mathbf{v})$  and used for the estimation of the intended movement.

The encoding parameters  $\mathbf{P} = \{f_1^{\text{off}}, \dots, f_{N_v}^{\text{off}}, f_1^{\text{mod}}, \dots, f_{N_v}^{\text{mod}}, \varphi_1, \dots, \varphi_{N_v}\}$

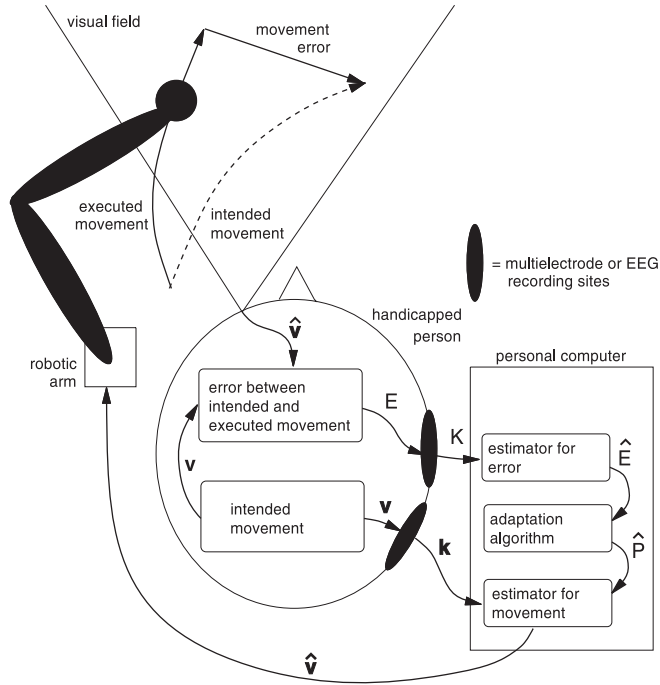


Fig. 1: Schematic view of the model. A handicapped subject is intending to execute a reach movement. The velocity  $\mathbf{v}$  of the intended movement is encoded in the spikes of neurons from motor cortex being recorded as a spike count vector  $\mathbf{k}$ .  $\mathbf{k}$  is fed into an algorithm utilizing the parameters  $\hat{\mathbf{P}}$  to make an estimation  $\hat{\mathbf{v}}$  of the intended movement.  $\hat{\mathbf{v}}$  is subsequently used to control a robotic arm executing the movement. The resulting mismatch  $E$  between intended and executed movement is perceived by the subject (to whom the originally intended movement is known), and encoded in error-monitoring brain regions. This error signal is simultaneously recorded by a second electrode array delivering a total spike count  $K$  from which an estimate  $\hat{E}$  of the original error is computed. Our adaptation algorithm employs a Monte-Carlo procedure for changing the parameters  $\hat{\mathbf{P}}$  of the motion estimator, seeking to improve the performance of the prosthesis by minimizing  $E$ .

are unknown to the estimation algorithm. Given the spike count vector  $\mathbf{k}$  and  $\mathbf{P}$ , the optimal linear Bayesian estimator for the minimum mean squared error between estimated velocity  $\hat{\mathbf{v}}$  and intended velocity  $\mathbf{v}$  would read

$$\hat{\mathbf{v}}(\mathbf{k}) = \sum_j^{N_v} \left( k_j - T \left( \frac{f_j^{\text{mod}}}{2} + f_j^{\text{off}} \right) \right) \mathbf{D}_j, \quad (1)$$

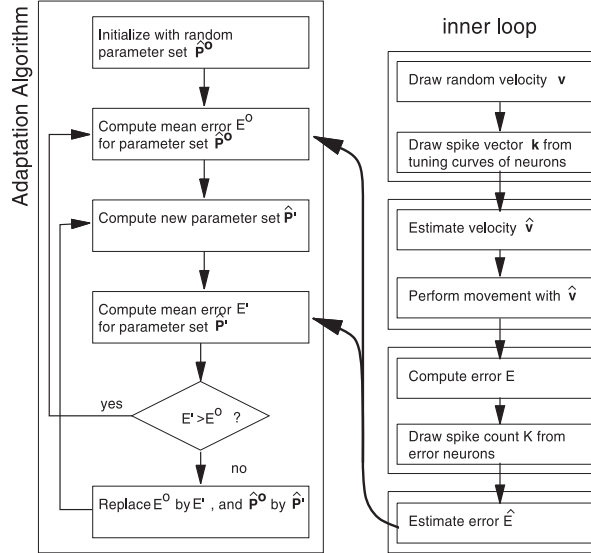


Fig. 2: Schematic diagram of the simulations. An 'inner loop' executed within each time interval  $T$  draws an intended movement velocity from a distribution, computes the corresponding spike counts of the velocity and error neurons, and performs the estimations of the velocity and error signals. The adaptation algorithm evaluates different parameter sets generated by a Monte-Carlo procedure, by averaging the error signal over a succession of periods  $T$ . Hereby, it realizes a stochastic gradient descent on the error signal  $E$ .

with the vector coefficients  $\mathbf{D}_j$  defined by <sup>1</sup>

$$\mathbf{D}_j = \sum_i^{N_v} f_i^{\text{mod}} v_{\text{max}} \{ \cos(\varphi_i), \sin(\varphi_i) \} \times \left[ \left\{ \frac{T}{2} f_i^{\text{mod}} f_j^{\text{mod}} \cos(\varphi_i - \varphi_j) + 8\delta_{i,j} \left( \frac{f_i^{\text{mod}}}{2} + f_i^{\text{off}} \right) \right\}^{-1} \right]_{i,j} \quad (2)$$

As the tuning properties  $\mathbf{P}$  of the neurons are unknown, the goal of the adaptation task is to find a close approximation  $\hat{\mathbf{P}}$  of  $\mathbf{P}$  which will then be used for estimation in Eqs.(1),(2).

The neural basis of error representation, error monitoring and error encoding is still a subject of intense research. The most useful signal would directly encode the difference between the target location (or speed) of an intended movement, and the actually executed movement of the prosthesis [5]. For our simulations we assume a monotonous linear dependency between the spiking activity of error-monitoring neurons and the observed error value.

<sup>1</sup> $[A_{ij}]^{-1}_{ij}$  denotes the matrix element in the  $i$ -th row of the  $j$ -th column of the inverse of the matrix comprising the components  $A_{ij}$ .

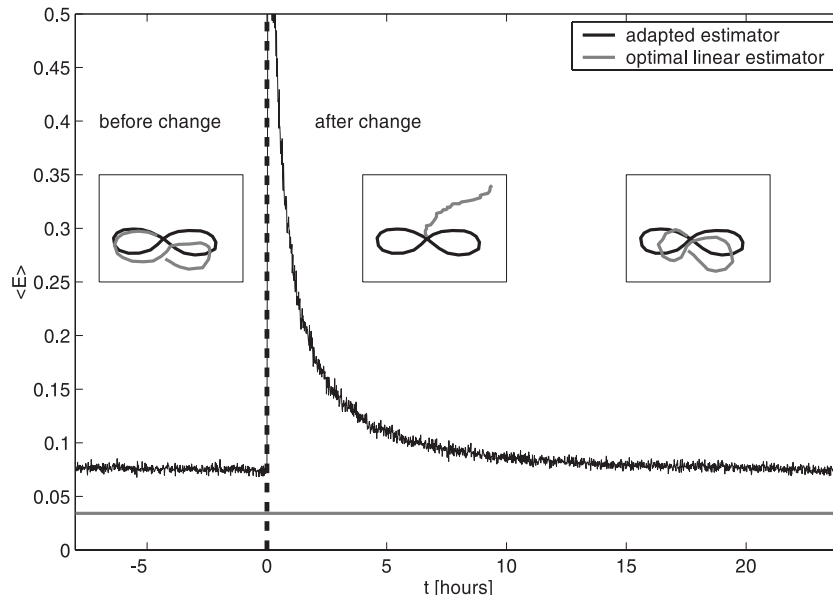


Fig. 3: Simulation demonstrating adaptation after a complete, radical change in neuronal tuning: the black curve shows the mean error  $\langle E \rangle$  in estimating intended velocity, averaged over 1000 trials (chance level is  $\approx 0.9$ ) with ongoing adaptation of estimation parameters during the full simulation period. Before  $t = 0$  the adaptation had reached a stationary state. At  $t = 0$  the tuning functions of the velocity coding neurons are completely re-initialized with random values. After some hours of re-adapting the estimator's parameters, the performance prior to the change has been restored. The horizontal grey line displays the minimal mean error achievable if the velocity estimation would have been made with the real tuning parameters. The three insets visualize the prosthetic's performance prior to the tuning change (left) where the decoding was almost perfect, immediately after the change (center), and 24 hours after the change (right). Adaptation has been successful if the estimated trajectory (in grey) closely approximates the intended trajectory (in black).

In detail, error-monitoring activity is modeled by the following equations: The difference between the intended movement  $\mathbf{v}$  and its estimate  $\hat{\mathbf{v}}$  is quantified by the squared error  $E(\mathbf{v}, \hat{\mathbf{v}}) = \sqrt{(v_x - \hat{v}_x)^2 + (v_y - \hat{v}_y)^2}$ . Challenging our algorithm with a worst case scenario, we assume that recordings are made from only  $N_E = 5$  neurons with similar tuning functions whose *population* firing rate is given by  $f_E(E) = F^{\text{off}} + F^{\text{mod}}E$ , with offset  $F^{\text{off}} = 25$  Hz and maximum rate modulation  $F^{\text{mod}} = 50$  Hz. This activity is observed as a stochastic spike count  $K$  drawn from a Poissonian distribution with mean  $f_E$ .

Our framework requires that recordings of the error signal are stable against

perturbations, in contrast to the recording of the intended movement signal. It follows that the parameters of the tuning function ( $F^{\text{mod}}$  and  $F^{\text{off}}$ ) for the population error signal have to be identified only once during the installation of the prosthesis. Under these conditions, the optimal (non-linear) estimator for the error is given by

$$\hat{E}(K) = \frac{\Gamma(2 + K, F^{\text{off}}, F^{\text{off}} + F^{\text{mod}})}{F^{\text{mod}}\Gamma(1 + K, F^{\text{off}}, F^{\text{off}} + F^{\text{mod}})} - \frac{F^{\text{off}}}{F^{\text{mod}}} \quad (3)$$

with  $\Gamma(k, a, b) = \int_a^b x^{k-1} \exp(-x) dx$  denoting the incomplete Gamma function.

### 3 Performance of Adaptation and Summary

Our main motivation for this study is to show that neural prostheses can successfully be adapted with an internal error signal, counteracting strong non-stationarities in neural coding and signal recording. For online adaptation, we employ a simple Monte-Carlo algorithm outlined in Fig.1. As a worst case scenario we simulated a complete change of the tuning properties of the motor cortical neurons (see Fig.3). The prediction error  $E$  instantly increased to values where a successful decoding of the intended movement was impossible (see center inset in Fig.3). However, with a half-life period of about 90 minutes, our algorithm re-adapts  $\hat{\mathbf{P}}$  and minimizes the decoding error thus restoring the previous performance. Therefore reconstruction of an intended movement was again possible after only a couple of hours adapting  $\hat{\mathbf{P}}$  (see rightmost inset in Fig.3).

Taken together, our results demonstrate that it is highly desirable to include error monitoring signals into neuro-prostheses. Our simulation demonstrates that typical error signals as present in various regions of the brain [6] can be used for on-line adaptation, preserving and enhancing the performance of a prosthesis subjected to non-stationarities. We therefore conclude that on-line adaptation of neuro-prostheses based on state-of-the art recordings is well within reach.

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